Income, Drugs and Health: Evidence from Russian Elderly Women

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ABSTRACT

Alica S. Sparling: Income, Drugs and Health: Evidence from Russian Elderly Women
(Under the direction of Donna B. Gilleskie)

This dissertation examines the effects of pension income and total household income on elderly Russian women's decision to obtain prescribed or recommended drugs and their subsequent health. The conceptual framework is a dynamic utility maximization problem that incorporates uncertain health and is based on concepts from the unitary model of household consumption and Grossman's model of the demand for health. The modeled outcomes include the probability of having drugs prescribed, the decision to obtain drugs and the health outcome, which are jointly estimated as a set of equations using the discrete factor approximation method that controls for individual, time-invariant unobserved heterogeneity. The sample is constructed from the Russia Longitudinal Monitoring Survey rounds between 1994 and 2002.

The study finds that income has a modest positive effect on health of Russian elderly women, but does not find evidence of income affecting their decision to obtain drugs. Contrary to the unitary model, the relative control over household resources matters because an increase in pension income has a much larger positive effect on the elderly woman's health than an increase in some other household member's income. This study also finds that obtaining all prescribed or recommended drugs lowers the probability of descending into bad health by 10 percentage points for women with good or average lagged self-assessed lagged health that were prescribed drugs, implying that drug therapy can be an effective form of disease management.

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CHAPTER 1

INTRODUCTION

1.1 Specific Aims

The objective of this study is to enhance our knowledge of the relationship between income, access to drugs and the health of elderly women. I address the effect of income on drug purchasing behavior and the effects of income and the decision to obtain drugs on health.

The relationship between income and health has been studied extensively by economists, and multiple reinforcing paths between income and health have been proposed. One obvious avenue that explains the causal relationship between income and health is access to medical care, which is enabled by higher income and leads to improved health. In my study I focus on a particular type of medical care, prescription drugs, which have been a rapidly growing component of medical care expenditures in the developed world. The total demand for drugs is significantly influenced by the drug demands of the elderly. The elderly are more likely than younger people to have multiple ailments and to rely on drugs to maintain their health, trusting that taking drugs as directed allows them to manage and possibly avoid further health complications. The possible benefits of drugs, in the face of rising medical care expenditures, underscore the importance of studying factors influencing the drug purchasing behavior of the elderly and the effect of their drug consumption on health.

This study investigates the relationship between income, access to drugs and health using a sample of Russian elderly women interviewed between 1994 and 2002. The sample includes only women because women and men exhibit differences in health trajectories and life expectancies, requiring separate analyses of their behavior and health outcomes. During the studied period Russia was (and still is) an environment of great resource constraint, which makes it a suitable setting for studying the access motive in the income-health gradient. Russia officially entitled all citizens to free medical care but not to free drugs. Most individuals paid for drugs out-of-pocket, although some qualified to receive government subsidies. Between 1994 and 1999, drug expenditures constituted over half of out-of-pocket medical care expenditures of an average Russian household (Besstremyannaya, 2002). Drug expenditures were found to be highly regressive, constituting 21 percent of the monthly income of the poorest households while only 5 percent for the wealthiest households (Feeley, 1999). Based on the survey used in this study, Russians increasingly complained about not being able to afford drugs: Zohoori, et al. (2001) note that the percent of elderly considering lack of money a reason for not obtaining medications rose from 24 percent in 1994 to 71 percent in 2000.

One of the study's aims is to isolate any differences between individual income effects and household income effects. I distinguish between these two types of income because the majority of elderly Russians live in households with at least one other adult. Thus their wellbeing and consumption is likely to be affected not only by their individual income but also by the total household income. Pension income is the most important component of the elderly person's individual income in Russia. More than 80 percent of the elderly's income comes from the government pension so I use this measure to investigate the effect of the elderly woman's individual income. A standard model of household resource allocation, the unitary model, suggests that households pool resources and that consumption of individual members depends on household's total income but not on individual members' contributions to it (Becker, 1981). I use a two-period variation of this model as a theoretical framework for my assessment of the importance of pension income versus total household income in elderly women's decisions to obtain drugs and maintain health. In order to test the household pooling hypothesis, I restrict my sample only to elderly women who live with other adults.

The elderly who face the decision of whether or not to obtain drugs first had drugs prescribed or recommended to them by someone in a medical institution. The probability of receiving a drug prescription or recommendation depends both on the doctor's assessment of the patient and the elderly woman's initiative to seek out medical help in the first place. The same characteristics of the elderly, such as unobserved health, attitudes to doctors or risk aversion, influence the probability of drug prescription and drug purchasing decisions. I therefore model the probability of drug prescription and address sample selection issues by jointly estimating drug prescription, drug purchase and health outcomes.

An important aim of this study is to measure the dynamic effect of income and the decision to obtain drugs on the elderly woman's ability to improve her health outcome over time. According to Grossman's model of health production, people's motivation for demanding medical services or drugs is derived from their demand for good health (Grossman, 1972). Using a two-period model I evaluate whether higher income and health investments influence future health outcome.

The study uses seven rounds of the Russia Longitudinal Monitoring Survey (RLMS) collected between 1994 and 2002. The RLMS offers comprehensive information on income, health and medical care, both at the household and individual levels. Seven rounds of observations and the breadth of information obtained give us a unique opportunity to study the income-health gradient and the decision to obtain drugs in order to gain insights for maintaining the health of the elderly. The panel character of the dataset also allows us to explore the appropriateness of panel data estimation techniques.

1.2. Contribution to Literature and Policy Relevance

This study makes several contributions. It tests the household resource pooling theory in a new setting of drug utilization in Russia. It makes an addition to the growing body of literature on access to health care and drug utilization in Russia. Dynamic modeling of the relationship between income, drug purchase decisions and health using a panel data set makes a contribution to the literature evaluating the benefits of income and health investments on health of the elderly. The study's findings can help policy makers assess whether targeted government transfers via pension income are efficient tools for improving the elderly people's access to medical care and drugs and health.

In spring 2005 Russian newspapers cautiously and foreign newspapers less cautiously covered upset reactions to a major change in Russian law pertaining to benefits enjoyed by many elderly. The new law that went into effect in January 2005 eliminated various Soviet-era established in-kind subsidies, which included free or discounted drugs for people with a doctor-board-approved status of an invalid. In place of these subsidies all elderly would receive a cash transfer. Many ordinary elderly Russians worried that the new law would lower their living standard. Demonstrations objecting to the new law occurred, and so far only a few regions have had the courage (and resources) to fully implement the new law. This study covers an earlier time period (1994-2002), but its design allow me to simulate what would have happened to the drug purchasing behavior and health of the elderly Russian women if such policy had been implemented during the studied period.

Another policy application of this study relates to understanding how household members in Russia share resources. Such understanding is essential for choosing appropriate policies for improving the elderly women's welfare. If households pool resources, then government policies aimed at transfers would not alter the household's resource allocation and can be neutral with respect to the household recipient of the transfer. It would not matter for improving the elderly person's welfare whether the source of the improvement was a higher pension, a lower labor income tax for working household members or a higher government child support payment. Conversely, if the relative control over resources in the household influences the allocation of these resources among household members, then increasing the elderly person's pension income would have a stronger positive effect on the elderly person's welfare than interventions targeting other household members or the household as a whole.

Last but not least, although this study looks at the effect of elderly people's drug consumption on health in Russia, its findings may also have policy relevance to the U.S. The Medicare Prescription Drug Bill has brought attention to the issues of effectiveness of drug use in improving general health. The financial burden of this program on taxpayers is extensive, making it important to understand the effect of drugs on health maintenance, and thus future utilization and costs of other Medicare covered services.

1.3. Overview of Chapters

The study is organized in the following chapters: Chapter 2 reviews literature on the relationship between income, drug utilization and health and on empirical tests of household resource pooling hypothesis, and it summarizes facts about Russia's health care and pension systems. Chapter 3 presents the conceptual framework, and Chapter 4 introduces the empirical framework. The sample used in the dissertation is described in Chapter 5. Results, which include both marginal direct and total effects and simulations of effects of selected policies, are presented in Chapter 6. Chapter 7 concludes and discusses limitations and potential future research.

CHAPTER 2

LITERATURE AND BACKGROUND

2.1. Relationship between Income, Drug Utilization and Health

The economic literature offers differing views on the merits of income and economic resources as determinants of increased medical care, drug utilization and health. Akin et al. (2001) point out that the effect of income on the demand for health services cannot be predicted in advance because an increase in income can lead to an improved health status not only through the increased capacity to purchase medical care, but also through purchases of other health-improving goods, which might actually lead to a drop of medical visits. Deaton and Paxson (1998) name several potential causal paths from income to health: poorer people have less access to health care, live and work in less healthy environments and are more prone to exhibit behaviors such as smoking or obesity. In addition to the effect of absolute income on health, more recent literature has also explored alternative reasons for the causal path from the socioeconomic status (SES) to health: income inequality, relative social rank, and elevated cumulated stress[1] (allostatic load), which is hypothesized to be higher for low SES (Smith 1999, Wilkinson 1996, Deaton and Paxson, 1998, 2001). A growing body of literature is also investigating the opposite causal link - leading from health to SES (Thomas and Strauss, 1997, Currie and Madrian, 1999, Dwyer and Mitchell 1999, Liu et al. 2003).

The angle, focus and methods of studies of the effect of income on health are very diverse. Ettner (1994) finds a positive effect of household income on self-assessed health and functional limitations. The author uses an instrumental variables method to control for the endogeneity of

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[1] Per Dr. Carey, MD, of C.Sheps Center in Chapel Hill, NC, stress leads to higher cortisol and noradrenergic hormones, which lead to greater cardiac risk.

household income in a cross-sectional study. Smith and Kington (2001) use ordered probits and a range of definitions of income and wealth to assess the effect of income on self-assessed health. They find that the income effects are nonlinear and most important in the poorest households and that different sources of income have different effects, and note that there is a compelling evidence of a strong causation link from health to income. In a more recent study, Adams et al. (2003) test the hypothesis of no direct causal link from socioeconomic status, which consists of wealth, income and residence variables, to mortality and health innovations of the elderly population. They find no direct causal link from SES to mortality and the incidence of sudden, acute conditions and some association of SES with incidence of gradual onset conditions, such as degenerative and chronic diseases. It is not clear, however, whether this association is due to a causal link or some common unobserved (genetic and behavioral) factors that affect both SES and health. Manning et al (1987) found small income effects on demand for out-patient medical care using the experimental data from the RAND Health Insurance Study. Smith (1999) ponders that especially at older ages, current economic resources may not have a quantitatively large impact on the current stock of health, because current health stock is a reflection of an entire history of incomes, health behaviors, prices and initial health endowments accumulated over years.

Newhouse (1993) using the RAND Health Insurance Study found that although lower insurance increased health services utilization, it had only minor effects on health outcomes. There has been some skepticism regarding small magnitudes of the effect of medical care on health outcomes in the US and other developed countries, sometimes coined as practice of "flat-of-the-curve" medicine.[2] However, many new medical treatments and drugs are dedicated to improving quality of life and relief of suffering rather than increasing longevity, which are hard to measure outcomes, which in turn may result in finding dissipated effects of treatments. Further, the problem

[2] "Flat-of-the-curve" medicine refers to the flat region of the health production curve. The total product curve exhibits the property of diminishing marginal returns to medical care. Eventually, at high quantities of medical care consumed, each additional unit of medical care leads only to a very small improvement in health outcome.

may apply to some treatments and drugs but not all (e.g. treatment of cardiovascular conditions). Russia, where less than 5 percent of GDP was devoted to health care during the studied period, is probably further away from the possibility of “flat-of-the-curve” medicine.

In Russia, Jensen and Richter (2003) look at the effect of income shocks on mortality and the use of medical services. They use a differences-in-differences model and find that pensioners with pension arrears in 1996 (i.e. who did not receive pension payments for at least a month during the pension crisis) declined their use of medical services and were more likely to die in the following two years. Stillman (2002) uses an instrumental variable method to estimate the effect of transitory income variation in Russia on energy intake, nutrition quality and BMI and finds an effect only on the diet composition. Both papers use the Russia Longitudinal Monitoring Survey.

Stillman and Thomas (2006) distinguish between the effect of permanent (longer-run) income, which they also associate with economic growth, and transitory household resources (income fluctuations) on nutritional status and assess whether low income households are able to smooth out income fluctuations. They focus on the same period as this study and associate the large income volatility with the effect of globalization. Household resources are proxied by household per capita non-durable expenditures.

The issue of access to medications by elderly people has received an increasing interest in the U.S. and has been addressed by a growing body of literature mainly in Canada and the United Kingdom (O’Brien, 1989, Grootendorst, 1995). These studies focus on effects of cost sharing and prices rather than income effects. In Russia, limited research has been published on drug utilization. Street et al. (1999) analyzed drug use of households in three Russian regions in 1996. The authors estimated the effect of discounts on the integer count of prescriptions purchased by the household using Poisson, Negative binomial, and Zero-altered negbin models, and the effect of discounts on drug expenditures using a two-part model. They found that full exemption from drug charges increases the number of prescriptions received by a household and reduces the probability of incurring expenditure. The authors found no evidence of a significant income effect on the receipt of prescriptions and drug expenditures.

2.2. Household Income Pooling

Consumption decisions, such as whether or not to buy drugs, of elderly living in extended households quite likely depend not only on their individual income but also on consumption and incomes of other household members. In such case it is more appropriate to analyze the elderly's consumption using the household rather than individual utility maximization framework. Several competing economic theories describe the household behavior. The most basic distinction is between the unitary model and game-theoretical models. The unitary model describes the household acting as a single unit. The competing models, such as collective and Nash bargaining models, assume that individual household members may have different preferences and arrive to the household resource allocation decisions via some bargaining process. The rejection of a unitary model implies that one of the alternative models should apply. However, due to extensive data requirements for testing the alternative models it has been difficult to assess which one of them, if any, more accurately describes household resource allocation than the unitary model.

The unitary model is easily tested and is a good starting point for comparisons with any other models, assuming that sufficient data exist to test the other models. Although the unitary model has been criticized as an "empirical straight-jacket" for household consumption (Vermeulen, 2000), it is a sufficient tool for assessing whether the source of income matters and provides useful information to policy makers whose aim is to improve wellbeing of the elderly, for example through their access to medical care or health. If only the total household income matters then any government policy that increases the household welfare will have the same effect on the elderly person's welfare as a targeted pension income increase. If not, then a government policy directly targeting the elderly would be more efficient in increasing the welfare of the elderly.

The unitary model allows us to analyze household utility maximization by using the same approach as for an individual utility maximization. The model has three testable implications: the Slutsky matrix is symmetric (i.e., marginal compensated wage changes have the same effect on each other's labor supply – Vermeulen, 2000), the Slutsky matrix is negative semidefinite, and the nonlabor income source has no effect on resource allocation (i.e. households pool resources). A test of the third, income pooling condition is conducted in this study.

The pooling hypothesis has been examined in several studies (e.g., Schultz, 1990, Thomas 1990) both for labor supply and consumption decisions. Lundberg et al. (1997) reject the pooling hypothesis in tests based on cross-sectional variation of income received by different household members (elderly parents and adult children, husbands and wives) but note that the tests may not be completely reliable because their income measures may not be exogenous to wages, prices and other determinants of consumption behavior. Altonji et al (1992) point out that one cannot fully control for the total household income if wage rates vary across members because changes in wages result both in income and substitution effects, and therefore effects of husband's earning's from wife's earnings in the unitary model can differ. Household income effect can be made independent of wages only by restricting preferences: the utility function must be either homogeneous or additively separable (Blundell 1986 and Browning et al. 1985).

Pezzin and Schone (1997) test the pooling restriction using a sample of 583 elderly residing with their adult children drawn from the Survey of Assets and Health Dynamics. The authors use Probit, Ordered Probit, Poisson and OLS methods to estimate the effect of the child's non-labor income on her labor supply, provision of informal care, parent's prescription drugs utilization and parent's doctor visits while controlling for total household non-labor income, parent's health and the child's demographic and sibling characteristics. The authors conclude that their sample does not behave consistently with the common preference, unitary models. Total non-labor household income had a negative effect on the number of prescription drugs demanded by the elderly parent, but the share controlled by a child had a significant positive effect. The authors also found a significant effect of the share of non-labor income controlled by the child on her labor supply and provision of informal care, which contradicts the prediction of the unitary model that the coefficient on the child's income is zero when controlling for household income. The authors found no income effects on parent's number of doctor visits, which they explained by Medicare subsidies available to all elderly.

Duflo (2002) found that an exogenous individual income shock had a positive effect on health of children in South Africa. She tested the unitary model by assessing whether the gender of the pension recipient in South Africa affects nutritional status of the grandchild and found that pensions received by women had a larger positive impact on the weight for height of girls, rejecting the pooling hypothesis. The author emphasized that a test of the unitary model requires a permanent exogenous change in income that happens after household formation.

Lundberg et al. (1997) took the advantage of a policy change in the UK that transferred a substantial child allowance from father (tax reduction on father's paycheck) to mother (direct cash payment) and compared family expenditures on men's, women's and children's clothing before and after the policy took effect. In the linear regression equations (both for before and after the policy change) the dependent variables are ratios of children's to men's clothing and women's to men's clothing. Independent variables of interest are three dummies representing the period after the policy change for different household sizes. Control variables are income (expenditures) and household composition measures. The authors found that a shift toward increased expenditures on children's and women's clothing relative to men's clothing occurred following the policy change transferring resources from husband to wife, and rejected the pooling hypothesis.

Tests of the unitary household model are particularly relevant to policymakers in Russia where almost 80 percent of the elderly women lived in households with other adults during the studied period.[3] In the context of Russia and in contrast to most studies, Jensen and Richter found no differential effects by gender of the elderly of their pension arrear vs. pension arrear of other household member on their health (2003).

[3] Source: RLMS dataset used in this study.

2.3. Background on Russia

Economy and Health Care in the 1990s

The study looks at a period marked by profound economic changes in the Russian Federation. Transition to market economy brought hyperinflation in 1991 that wiped out many people's savings, freeing of wages and most prices in 1992, privatization of state-owned companies, pension crisis with the problem of pension arrears in 1996, and a financial crisis in the fall of 1998, during which the real GDP fell by 10 to 15 percent over a very short time period.

Russia spent spends 4.3 percent of GDP on health care in 1995, a number that steadily declined to 2.9 percent in 2000 (UNECE 2003).[4] During the studied period, the Russian health care system underwent decentralization and financial restructuring. Free medical care continued to be guaranteed by Russia's constitution, but it was impossible to be delivered due to the lack of funding collected from the traditional general taxation and the new compulsory health insurance system.[5] The cost of new treatments and drugs increased in the 1990s, but its funding from the public sources fell by one third (Shishkin 2000). Inadequate funds had a striking effect on hospitals struggling to continue to provide free hospitalization. Many hospitals began to request that patients buy and bring their own drugs and supplies like bandages. Some polyclinics (physician offices providing out-patient services) initiated co-pays for services such as x-rays. Reports of unofficial under-the-table payments both in hospitals and polyclinics were abundant, ranging from simple boxes of chocolates to expensive surgery payments.

[4] In 2000, the percent of GDP spent on health care was around 8 percent in most EU countries and above 13 percent in the US. (http://www.unece.org/stats/trends/ch6/6.15.xls)

[5] Traditionally, health care was funded by general taxation. In 1993 a compulsory social/state medical insurance was adopted, funded by statutory employers' contributions (World Health Organization, "Highlights on health in the Russian federation," 1999). In 1997, insurance covered over one third of all expenditures, and in 1998, 87 percent of the total population was insured. However, the source of funding of health care – general taxation versus compulsory insurance - was irrelevant to the decision making of the elderly at the time of this study.

The pharmaceutical sector has also changed radically since the early 1990s. Domestic production of drugs collapsed and drug imports have proliferated. Consumer drug selection and drug prices increased. Private pharmacies began to compete for clients against state pharmacies. There was an abundance of pharmacies in urban areas, and to attract clientele pharmacies often offered 5 to 12 percent marketing discounts to seniors.[6]

Although Russia did not provide drug benefits specifically geared to the elderly or the low income group, elderly individuals could receive either a 100 or 50 percent drug price discounts if they belonged to one of the government-designated categories of patients (e.g. disabled, war veterans, Chernobyl survivors) or diseases (e.g., cancer, diabetes, bronchial asthma, recovery period up to six months after myocardial infarction). These categories were grandfathered from the Soviet times when people also paid for drugs out-of-pocket unless they qualified for exemptions from charges. Elderly individuals eligible for discounts most often belonged either to the war veteran category or the disabled category. The assignment of the disability ("invalid") status was constrained by federal guidelines. Three types of disability groups defined by the Law of State Pensions of RU were Category 1, consisting of people permanently disabled and incapable of work who require constant attendance; Category 2, consisting of people incapable of work but who do not require constant attendance; and Category 3, consisting of people partially disabled and 50 percent incapable of work (Becker and Merkuryeva 2003). Each applicant's eligibility, as well as prescribed discounted drugs, were determined by the local certified board of physicians, who based their decisions on each patient's comorbidities.

The Ministerial Order from 1994 updated categories of citizens and diseases that qualified for discounts on the approved formulary of essential drugs. Street (1999) noted that this government decree from 1994 gave regions (called oblasts) autonomy in determining exempted drugs, eligibility requirements and reimbursement levels. I found that the exemption rules for invalids, war veterans

[6] Pharmacists whom I interviewed in commercial and social pharmacies in Saratov, Novgorod and St. Petersburg, considered prices across competing pharmacies comparable.

and victims of Chernobyl were honored across regions, most likely because their drugs received federal funding.[7] I found regional differences in granting discounts based on specific disease categories. Per manager of one of the Novgorod pharmacies, drugs in these disease-specific categories were funded from municipal budgets.

In each district, only several assigned pharmacies, called “social” pharmacies, had the right to dispense discounted drugs to eligible patients.[8] Discounted drugs were dispensed only on prescription and were carefully tracked. Patients were required to obtain a new prescription for drug refills from their polyclinic on a monthly basis. I found from anecdotal evidence that some eligible individuals were discouraged from taking advantage of discounted drugs because of the time costs associated with getting the refill prescription and traveling to a social pharmacy, which could be located far from the polyclinic, and because many drugs were not on the government’s formulary and thus did not qualify for a discount. So, instead individuals eligible for discounts chose to buy drugs in a commercial pharmacy.

In January 20006 a new law replacing the system of providing discounted drugs to selected groups with cash payments to all elderly came into effect. The law lead to many protests and resulted in pension hikes to compensate recipients of discounted drugs, such as invalids and veterans, many of whom are elderly.

Pension system

The most important source of the elderly person’s individual income is pension, constituting more than 80 percent of the person’s individual income. After the financial crisis of 1998, real

[7] In summer of 2003 I took a one-month field research trip to Russia to learn about the Russian health care system, funded by the Sheps Center International travel scholarship. During this trip I visited hospitals, policlinics, pharmacies and research institutes, and interviewed doctors, pharmacists, administrators and researchers in four cities (Moscow, Saratov, St.Petersburg and Velikij Novgorod).

[8] These social pharmacies were selected by local governments through tenders and dispensed discounted drugs supplied by the government at separate counters from commercial drugs. The lure to compete for the social pharmacy status was the government’s payment of 3 percent of the value of the dispensed drugs, a guarantee of a 90 percent discount on property rent, and a regular stream of customers qualifying for discounts. Approximately two to three social pharmacies were in place per district with 100,000 inhabitants.

pension fell to only 30 percent of its real value in 1990 (Gurvich 2002). Mroz et al. (2001) report that although in mid 1990's pension-aged individuals were less likely to live in households with income below the regional poverty lines than individuals in other age groups, poverty rates of the elderly increased more than those of any other group: from 6.7 percent in 1992 to 30.6 percent in 1996. The poverty rates of the elderly then fell to 25 percent in 1998 and 15 percent in 2000. The authors contemplate that this development could be a reflection of an increase in pension income between 1998 and 2000.

Russia has a mandatory, almost universal pay-as-you-go public pension system (Sinyavskaya, 2004). The rules for the old age and service pensions originate in the 1956 Soviet pension law (Lushkina, 2001). Women with 20 years of service and at least 55 years old, and men with 25 years of service and at least 60 years old qualify to receive pension. In this study, the sample of "elderly women" includes all women at least 55 years old who reported receiving pension income. This definition thus represents a younger group than is typically considered as elderly in U.S. studies.

Some people, such as workers in unfavorable conditions, may qualify for earlier retirement. The 1990 pension law states that pension can be between 55 and 75 percent of the wage base, which is the average individual salary for the last two or any continuous five years of service (Sinayavskaya (2004), Luxembourg Income Study). On top of the initial 55 percent replacement rate of the wage base the elderly gets an additional 1 percent increase in pension for each additional year of service up to 75 percent of salary. The pension amount is loosely indexed against inflation and the minimum pension is not supposed to fall below the minimum wage. The elderly receiving pension were allowed to work without any restrictions in hours worked or salary. Jensen and Richter (2003) note that as of 1996 the pension eligibility was not affected by current employment status.

Jensen and Richter (2003) summarized how the pension system functioned in 1996. The age-qualified individuals (26 percent of Russia's population in 1996) received pension in form of monthly cash transfers from the Pension Fund of Russia. The Pension Fund's decentralized system consisted of one federal, 80 regional and 2342 local departments in 1996 and was financed from a payroll tax.

Regional offices collected the revenue, made payments to its pensioners and forwarded any surplus to the central fund, which then redistributed the funds to 'debtor' regions. In 1996, there were 15 'donor' regions and 74 'debtor' regions. 1996 was a year of decreased economic output in Russia, which translated into the government's problems with collection of funds for pensions. The result was that many pensioners faced pension payment lags. Pension arrears reported by the respondents of the Russian Longitudinal Monitoring Survey were 33 percent in 1996 and fell to 15 percent in 1998. Officially, the pension arrear problem was solved in 1999, per statement of M. Zurabov, chief of Russia's Pension Fund.

About 4.2 percent of all pension-age women and 10 percent of all pension-age men in the RLMS claimed to receive a disability pension in 2001.[9] To receive the benefit the disabled person must have worked a minimum of 1 to 15 years before the onset of disability. Disability categories 1 and 2 received 75 percent of wage base and Category 3 received 30 percent of the wage base (Becker and Merkuryeva 2003). If information on individual wage base was unavailable then disabled in Categories 1 and 2 received pension equal to the minimum old-age pension and disabled in Gategory 3 2/3 of the minimum old-age pension. The same minimum and maximum pension amounts applied both for the disability pension and the old age pension. Category 1 received an additional supplement for constant attendance (Luxembourg Income Study).

People eligible for disability pensions also qualified for drug discounts, free transportation and discounted utilities. Becker and Merkuryeva state that these benefits double pensioners' real income (their source is FBEA 1998) and give an incentive for the elderly (and others as well) to apply the disability status. Sinayavskaya (2004) notes that upon reaching the pension age people could choose to change the status of disability pension to old age pension if the latter was higher. According to Becker and Merkuryeva (2003) average Russian disability pension is 10 percent lower than old-age pension, which leads to the switch of disability pension to old-age pension upon reaching the pension age, while continuing to use other disability perks.

[99] These figures were lower before 2000 when the question about pension type was phrased differently.

CHAPTER 3

THEORETICAL MODEL

The theoretical model depicts the relationship between income, health investments and the health outcome of an elderly woman. The conceptual framework is a two-period household utility maximization problem that incorporates the uncertain health of its members. The elderly woman's decisions are considered to be part of the household's optimization problem. The theoretical model is based on concepts from Grossman's (1972) model of the demand for health and Becker's (1981) unitary model of household consumption. In Sections 3.1 and 3.2 I briefly describe parts of these two models that directly relate to this study's model of behavior. The theoretical model is described in Sections 3.3 and 3.4. I present testable hypotheses derived from the model in Section 3.5.

3.1. Motivation: Grossman' Model of Demand for Health

Grossman (1972) introduced the economic concept of the commodity "health," where health is viewed both as a consumption good and an investment good. Health increases the individual's utility in two ways: by making him feel better (consumption aspect), and by increasing the number of days available for work and other productive activities in the subsequent periods, thus affecting the individual's future income and consumption of all other commodities (investment aspect).

An individual receives utility from the composite consumption commodity Z_t and healthy days h_t. The individual maximizes lifetime utility $U(h_0, h_1, h_2, \ldots, h_T, Z_0, Z_1, Z_2, \ldots Z_T)$ subject to the lifetime budget constraint, ime constraint, and production functions for h and Z. Both healthy days h and the commodity Z are assumed to increase utility at a decreasing rate ($U_h > 0$, $U_{hh} < 0$, $U_z > 0$ and

$U_{zz}<0)$. Healthy days h_t are considered a flow of services produced from an accumulated health stock H_t where $h_t = f(H_t)$, ($f'>0\, f''<0$). Each time period, the health stock H_t depreciates at rate δ_t, but this depreciation can be alleviated by making an investment I_t in health. The health stock in the following period is then determined in the health production function $H_{t+1} = H_t - \delta_t H_t + I_t$.

The gross investment in health, $I_t = g(m_t, T^H_t; E_t)$ is a function of health-producing medical care m_t , time spent in the m_t activity, and the human capital E_t. The demand for medical care is a derived demand because individuals do not receive utility from health investments directly; instead the benefit of health investments is realized as an improved health stock in the future, allowing for more productive time in the future.

At an older age, health depreciates faster than at a younger age. To produce the optimal health stock, elderly people increase their gross investment in health, which includes the use of medical services. At some point, however, the cost of maintaining one's health stock increases too rapidly and it becomes optimal to let health fall and eventually reach a level corresponding to death at time T.

3.2. Motivation: Becker's Unitary Model

The traditional approach that reconciles the individual's behavior with a household behavior is the unitary model, also referred to as the neoclassical or common preference model. According to this model, a household pools income from all its members and the distribution of consumption depends only on the total household income. The source of income is irrelevant to the household's allocation decisions. Thus, an elderly woman's drug consumption and health would be influenced only by the total income of her household, but not by the share of her contribution to it.

Samuelson (1956) and Becker (1981) developed two different motivations for the household behavior in the unitary model. Becker assumes that an altruistic household head (a dictator) makes transfers to supplement income of members in need. Samuelson assumes that all household members have the same preferences and arrive at the optimal resource allocation by consensus. Thomas (1990) states that the assumption of the same preferences of all household members and the assumption of the dictator are observationally equivalent for the purposes of testing the household income pooling hypothesis. I use Becker's approach as a blueprint for my theoretical framework.

In Becker's (1981) unitary model the household head is an effective altruist, and his utility depends positively on the utility of other household members. If the household consists only of the altruistic household head *A* and one other household member (e.g. elderly woman *E*) then the household head's utility function is $U^A = U\left[Z^A, \psi(U^E)\right]$ where $\frac{\partial U^A}{\partial U^E} > 0$, and ψ *>0* is a function of the other household member's utility U^E. [10]

The altruists' behavior is altered by his altruism: he does not consume at his endowment point but transfers a positive part of his income to other household member. He consumes $Z^A = Y^A - T$, which is equal to his income Y^A less the contribution *T* made to the other household member *E*. Price of Z is set to one. The altruist's contribution allows the household member's consumption to be $Z^E = Y^E + T$.

The altruist maximizes his utility U^A subject to the household budget constraint $Z^A + Z^E = Y^A + Y^E = S$ where *S* is the total household income. The equilibrium condition for the altruist's allocation of resources is $\frac{\partial U^A / \partial Z^A}{\partial U^A / \partial Z^E} = 1$. In equilibrium, the altruist receives the same marginal utility from his own consumption as from the consumption of the other member *E*. The equilibrium condition gives us the household head's demand functions $Z^A = Z^A(S)$ and $Z^E = Z^E(S)$.

If the other household member *E* is selfish she maximizes $U^E = U(Z^E)$ subject to her budget constraint $S^* = Z^E = Y^E + T$ where S* is her allocated share of the household income and

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[10] Implications of the model continue to hold when more than two household members (Becker 1981).

Y^E is her individual income (e.g. pension income). It is in her interest to maximize the household income *S* because then her utility is maximized too; thus she appears to act altruistically towards the altruistic head (known as the Rotten Kid Theorem). The household member *E* would refrain from any actions that would raise her income by less than the resulting fall in *T* received from the altruistic head.

However, if the selfish *E* increases her income to the point where the contribution *T* is eliminated then the altruist no longer maximizes the household income. Maximization of the household income is more likely to occur if *E* is also altruistic and makes contributions to the altruistic *A* if her income is sufficiently large relative to altruist *A*. Maximization of the household income would also always occur if household members have the same utility function.

3.3. Theoretical Model – Household Head's Optimization Problem

The theoretical model is motivated both by Grossman's model of demand for health, in which demand for medical care is demand derived from our demand for health, and Becker's unitary model, in which a household pools resources.

In this model, the household (i.e. the effective altruistic household head *A*) maximizes a two-period household utility function subject to (1) the total household income budget constraint (S_1 and S_2), (2) health production functions h_t^i, (3) the commodity Z_t^i production functions, and (4) the time constraints $\Omega_{i,t}$ Subscripts *i=1..N* refer to household members, one of whom is *E* = the elderly woman of interest in this study, and *t=1, 2* refer to the two time periods.

Household members receive utility from a composite consumption commodity ($Z_{i,1}, Z_{i,2}$) and health ($h_{i,1}, h_{i,2}$) in each period 1 and 2, where $U_h > 0$ $U_{hh} < 0$, $U_z > 0$ *and* $U_{zz} < 0$. Total household income in Periods 1 and 2 (S_1, S_2) is the sum of all members' labor income (wages *w)* and non-labor income (*y,* e.g. pension income) in the respective periods. In period 1, S_1 equals the sum of household members' expenditures on *X* used to produce the composite commodity *Z* and expenditures on medical services *m* used to produce health. In Period 2, household income S_2 equals the expenditures on *X* because in this two-period model we assume that household members invest in health only in the first period (so $m_{i,2} = 0$).

The two-period household utility function

$$U^A[Z_1^A, h_1^A, U^E(Z_1^E, h_1^E), U^3(Z_1^3, h_1^3), ..., U^N(Z_1^N, h_1^N)] \qquad \text{Period 1}$$

$$+\delta E[U^A[Z_2^A, h_2^A, U^E(Z_2^E, h_2^E), U^3(Z_2^3, h_2^3), .., U^N(Z_2^N, h_2^N)]] \qquad \text{Period 2}$$

is maximized subject to

(1) the total household income budget constraint,

$$S_1 = \sum_{i=1}^{N} X_1^i + m_1^i = \sum_{i=1}^{N} w_1^i \times T_1^{Wi} + \sum_{i=1}^{N} y_1^i \qquad \text{Period 1}$$

$$S_2 = \sum_{i=1}^{N} X_2^i = \sum_{i=1}^{N} w_2^i \times T_2^{Wi} + \sum_{i=1}^{N} y_2^i \qquad \text{Period 2}$$

(2) the health production functions,

h_1^i is exogenous Period 1

$$h_2^i = f_i(m_2^i, T_2^{Hi}; h_2^i) \qquad \text{Period 2}$$

where $\partial h_2^i / \partial m_1^i > 0$, $\partial^2 h_{i,2} / \partial m_{i,1}^2 < 0$; $\partial h_t^i / \partial T_t^{Hi} > 0$

(3) the commodity *Z* production functions,

$Z_t^i = f^i(X_t^i, T_t^{Zi}; h_t^i)$ where $\partial T_t^{Zi} / \partial h_t^i > 0$, $\partial Z_t^i / \partial T_t^{Zi} > 0$, and *t*=1, 2 Period 1, 2

(4) and the time constraints.

$\Omega_{i,t} = T_{i,t} = T_{i,t}^L + T_{i,t}^Z + T_{i,t}^W + T_{i,t}^H$ where $T_{i,2}^H = 0$, $\partial T_{i,t}^L / \partial h_{i,t} < 0$, *t*=1, 2 Period 1, 2

In Period 1, health ($h_{i,1}$) is given, exogenous. Each household member makes a health investment in medical care, $m_{i,1}$ and spends time on health producing activities $T_{i,1}^{H}$. In Period 2, health $h_{i,2}$ is endogenous; it is a function of the investment in health $m_{i,1}$ and $T_{i,1}^{H}$ made in Period 1 and depends also on the exogenous $h_{i,1}$.

Each time period, each household member has a fixed total amount of time (Ω) available, which is divided between work, health producing activities, commodity Z producing activities and time lost due to illness. δ is a time discount factor. By assumption, the utility function is additive and separable. Commodities ($Z_{i,1}, Z_{i,2}$) and health ($h_{i,1}, h_{i,2}$) are normal goods.[11]

3.4. Theoretical Model – Elderly Woman's Optimization Problem

Assuming that the altruistic household head (*A)* allocates household resources among house members by making transfers and that the elderly woman is a selfish household member, we can write down the elderly woman's optimization problem. The elderly woman maximizes a two-period utility function subject to the budget constraint allocated to her by the altruist *(S*)* and subject o her health production function and the commodity *Z* production function.

I assume that the she is out of the labor force (T_1^W =0) and receives pension income from the government (non-labor income *y*). I further assume that only two states of health are possible: good health (h^G) or bad health (h^B). The focus of this study is the elderly woman's decision to obtain drugs; thus I assume that m_1 represents drug consumption and it is the only health investment in the elderly woman's optimization problem (which means that T_1^H =0 and $T = T_1^Z$).

In each time period, the elderly woman receives utility from health *h* and the composite commodity *Z*. Following the unitary model, S_1^* and S_2^* are fixed money amounts allocated to her by

[11] There is no saving or borrowing in this model. If added, we would need only one budget constraint, with Period 2 components discounted by interest rate.

the altruistic household head *(A)* from the total household income (S_1, S_2) . In Period 2, the elderly woman's health h_2 is stochastic. The probability *p* of health h_2 in Period 2 depends on the previous period's health h_1 and the health investment m_1.

$$\max \qquad \underbrace{U(Z_1, h_1)}_{\text{Period 1}} + \underbrace{\delta\left[\sum_{h'=G,B} p(h_2 = h' \mid m_1, h_1) U(Z_2, h_2)\right]}_{\text{Period 2}}$$

subject to

$S_1^* = X_1 + m_1$ Period 1

$S_2^* = X_2$ Period 2

$h_2 = f\ (m_1; h_1)$ Period 2

$Z_t = f\ (X_t; h_t)$, *t=1, 2* Period 1

The elderly woman's choice variables are *m* and *X*. In this study, the variable of interest is drug consumption m_1 in Period 1. It affects the elderly woman's utility in two ways. On one hand, drug consumption reduces the amount of income available for consumption of good X_1 in Period 1, which lowers utility in Period 1. On the other hand, drug consumption increases the probability of health h_2 being good (h^G) and thus increases utility in Period 2.

The first order condition ($\frac{\partial U}{\partial m_1} = 0$) derived from the elderly woman's utility maximization problem states that when the elderly woman optimally allocates resources between *m* and *X,* the negative marginal utility of m_1 in Period 1 equals the expected marginal utility of m_1 in Period 2.

$$-\frac{\partial U(Z_1[S_1^* - m_1], h_1)}{\partial m_1} = \delta\left[U(Z_2, h_{2H}^*) - U(Z_2, h_{2L}^*)\right]\frac{\partial p(h_2 = h^G \mid m_1, h_1)}{\partial m_1}$$

The effect of the drug consumption m_1 on the probability of good health $p(h_2 = h^G \mid m_1, h_1)$ in Period 2 is considered positive because health investments, such as drug consumptions, are input in the health production function, and I assume that individuals make health investments only if they increase the probability of being in good health in the future.

We can sign the effect of an increase in income S_1^* on drug consumption m_1 and the probability of good health p($h_2 = h^G$). If we assume that *m* and *h* are normal goods then an increase in income (S_1^* *)* will lead to an increase in m_1 and better health in Period 2.

$$\frac{\partial m_1}{\partial S_1^*} = -\frac{-\dfrac{\partial^2 U(Z_1, h_1)}{\partial m_1^2}}{\dfrac{\partial^2 U(Z_1, h_1)}{\partial m_1^2} + \delta^2 \left[U(Z_2, h_{2H}^*) - U(Z_2, h_{2L}^*)\right]^2 \dfrac{\partial^2 p(h_2 = h^G \mid m_1, h_1)}{\partial m_1^2}} > 0$$

$$\frac{\partial p(h_2 = h^G \mid m_1, h_1)}{\partial S_1^*} = \frac{\partial p(h_2 = h^G \mid m_1, h_1)}{\partial m_1} * \frac{\partial m_1}{\partial S_1^*} > 0$$

Assuming that an increase in total household income (S_1) leads to an increase in the income allocated to the elderly in the unitary household model (S_1^*), then the marginal effect of increasing total household income (S_1) on drug consumption is positive too: $\dfrac{\partial m_1}{\partial S_1} = \dfrac{\partial m_1}{\partial S_1^*} \dfrac{\partial S_1^*}{\partial S_1} > 0$.

3.5. Hypotheses

The theoretical model leads to the following empirically testable hypotheses:

Hypothesis 1: An increase in the Period 1 household income has no effect on the elderly person's spending on health investment (such as drug utilization).

$$H_0: \ \frac{\partial m_1}{\partial S_1} = 0 \qquad \text{versus} \quad H_A: \ \frac{\partial m_1}{\partial S_1} \neq 0$$

Hypothesis 2: Health investment (such as drug utilization), holding prices and wages constant, is a function of the total household income. The elderly person's resource control (pension y_1), controlling for total household income, has no additional effect.

$$H_0: \ m_1 = f(S_1) \qquad \text{versus} \quad H_A: \ m_1 = g(S_1, y_1)$$

$$\text{thus} \ \frac{\partial m_1}{\partial y_1} = 0 \qquad \text{thus} \ \frac{\partial m_1}{\partial y_1} \neq 0$$

Hypothesis 3: An increase in the Period 1 household income has no effect on the probability of the elderly person's health being good in Period 2.

$$H_0: \ \frac{\partial p(h_2 = h^G \mid m_1, h_1)}{\partial S_1} = 0 \qquad \text{versus} \quad H_A: \ \frac{\partial p(h_2 = h^G \mid m_1, h_1)}{\partial S_1} \neq 0$$

Hypothesis 4: The probability of being in good health, holding prices and wages constant, is a function of the total household income. The elderly person's resource control (pension y_1), controlling for total household income, has no additional effect.

$$H_0: \ p(h_2 = h^G \mid m_1, h_1) = f(S_1) \qquad \text{vs.} \ H_A: \ p(h_2 = h^G \mid m_1, h_1) = f(S_1, y_1)$$

$$\text{thus} \ \frac{\partial p}{\partial y_1} = 0 \qquad \text{thus} \ \frac{\partial p}{\partial y_1} \neq 0$$

CHAPTER 4

EMPIRICAL FRAMEWORK

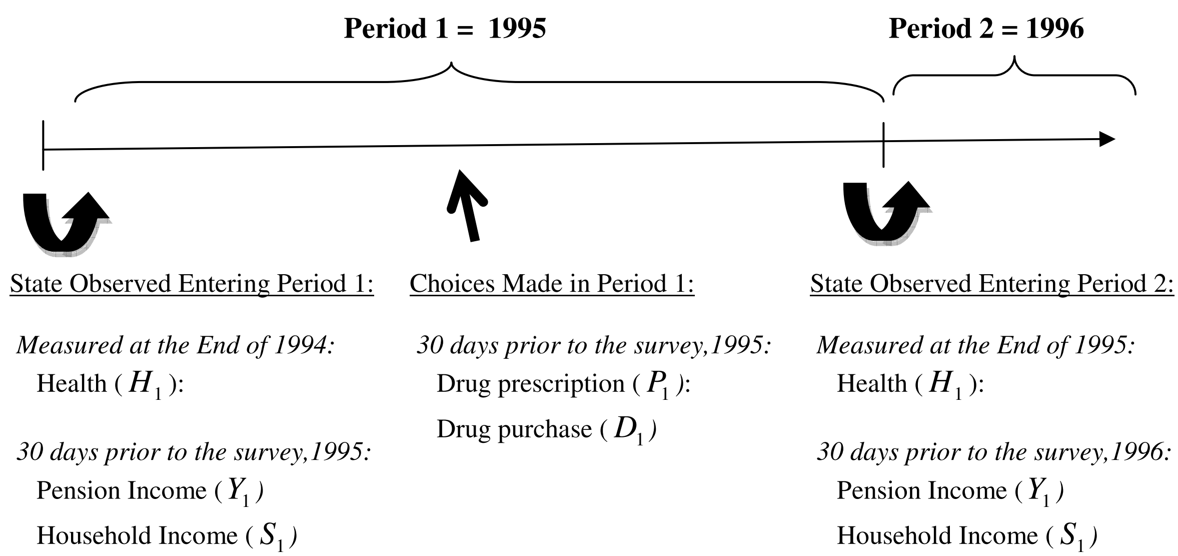
To test the hypothesized effects of income on the decision to obtain drugs and health derived from the theoretical model, the empirical model jointly estimates one selection equation (drug prescription), one demand equation (drug purchase) and one production function (health outcome). The dependent variables are functions of pension income, household income, lagged health, a set of individual and community characteristics and time and regional controls. The preferred estimation method is the discrete factor approximation method that controls for individual, time-invariant unobserved heterogeneity.

In Section 4.1 I describe the individual's decision making process in the context of the available data in order to bridge the theoretical model with the empirical model. In Section 4.2 I discuss the unobserved heterogeneity in my sample and present specifications of the individual equations in the preferred model. In Sections 4.3 and 4.4 I describe the discrete factor approximation method and the model's identification restrictions. In Section 4.5 I introduce alternative estimation methods used for comparisons of results with the preferred method.

4.1. Behavioral Decision Making Process

The empirical model follows the theoretical model while taking into account the particulars of the available data for Russian elderly women. Figure 4.1 shows how the timing of measurement of the key variables in the RLMS survey corresponds to the theoretical model's Periods 1 and 2.

Figure 4.1: Key Variables in the Theoretical Model and RLMS



In this example, year 1995 corresponds to Period 1 in the theoretical model and 1996 to Period 2. The elderly woman enters Period 1 with the health stock (H_1) inherited from the previous period, measured in this study as self-assessed health. She observes her pension income (Y_1) and the household income (S_1) at the beginning of Period 1. In Period 1, the elderly woman may be prescribed drugs or recommended to obtain drugs by a health professional in a medical institution (P_1). Conditional on having drugs prescribed or recommended, she then decides whether to make a health investment and obtain these drugs (D_1). The elderly woman enters Period 2 with an updated health stock (H_2).

4.2. Equation Specification

4.2.1. Modeling Unobserved Heterogeneity

There are several reasons why when investigating the relationship between income, drug purchase and the health outcome we should assume that the unobserved components of the selection (drug prescription), demand (drug purchase) and production (health outcome) equations are not independent. Ignoring unobserved heterogeneity of the sample would lead to biased estimates. The preferred model used in this study mitigates bias from the following sources: endogeneity of health in the drug prescription, drug purchase and health outcome estimation, endogeneity of drug prescription, drug purchase in the health outcome estimation, and selection bias in the drug purchase estimation.

In the theoretical model (Section 3.4) and its behavioral counterpart (Section 4.1), health stock is a function of lagged health and health investment (the decision to obtain drugs) made in the previous period. The decision to purchase drugs is a function of lagged health and permanent, individual unobserved characteristics influencing both health and the drug purchase decisions. Thus the decision to purchase drugs should be treated as an endogenous explanatory variable in the health production function.

When we extend the conceptual framework beyond two periods, it follows that the lagged health itself must be a function of health and health investments made in earlier periods, making it an endogenous explanatory variable in the health production function too. While the use of a lagged health measure in the estimation of drug purchase would eliminate the problem of reverse causality, lagged health continues to be endogenous in the drug purchase equation due to the presence of individual unobserved characteristics affecting both health and health investment decisions.

Last but not least, the RLMS survey collects data on the drug purchasing behavior only for those individuals who report having drugs prescribed to them, which may lead to the selection problem. Such problem arises if there is a systematic difference between individuals in the subset with a drugs prescription and the subset without it because the selection into the two subsets was not random with respect to the outcome (Jones 2000, Heckman 1979). In such case any estimates obtained from only one subset would not be representative of the full sample. It is quite possible that people with drug prescription have certain unobserved characteristics that the other group lacks. For example, their unobserved health may be worse or, conditional on the same health, they may trust their doctors and health care system more or place a higher value on their health than those people who were not prescribed drugs. Because of these reasons, they may be more likely both to seek out medical care leading to more opportunities to have drugs prescribed as well as obtain all prescribed drugs.[12]

The presence of unobserved heterogeneity means that the drug prescription, drug purchase and health outcome equations have correlated error terms and should be estimated jointly. In the jointly estimated model used in this study, the individual's permanent unobserved heterogeneity (μ) enters all equations as a random effect explanatory variable. It serves as a proxy for the individual's characteristics that do not vary over time, such as certain aspects of unobserved health, genetic disposition to disease, health preferences, risk aversion and attitudes towards the health care system. For example, an elderly person highly risk averse about health is more likely to seek out medical care to treat a health problem, obtain prescribed drugs and make lifestyle decisions that help maintain her health.[13]

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[12] Lundberg et al. (1997) note that labor income should not be included in testing the pooling restriction because hours worked by household members are simultaneously determined with the household consumption choices. However, in this study, I assume that income and the living arrangement are exogenous and determined outside of the model. This assumption should be relaxed and examined by future research. The same unobserved characteristics may have affected both health and past labor supply and earnings of the individual - and therefore today's pension, as well as the elderly's decision to live in an extended household with an adult child, and other household members' labor supply decisions, which in turn affect household income.

[13] An earlier version of the model included also time-variant unobserved individual heterogeneity ν_t, which would capture, for example, unobserved natural aging and the health deterioration rate. The estimation results though indicated that including this type of unobserved heterogeneity did not improve log likelihood.

The error term ε_t^e for each equation *e* where *e=H, D, P,* consists of two parts $\varepsilon_t^e = \rho^e \mu + u_t^e$. In each equation, the coefficient ρ^e is the factor loading on the permanent unobserved effect μ and is estimated as one of the parameters in the set of equations. The coefficient ρ^e represents the correlation of each equation with the unobserved heterogeneity term, and its value varies from equation to equation. The component *u* of the error term is an independent mean zero error term that is distributed logistically as the dependent variables are dichotomous outcomes as explained in Sections 4.2.2 and 4.2.4. The discrete factor analysis used to estimate this model with unobserved heterogeneity is described in Section 4.4 of this chapter.

4.2.2. Drug Prescription and Drug Purchase Equations

An individual enters each period having inherited their health stock H_t from the end of the previous period. She also observes household income Y_t^{HH} and pension income Y_t^E. Then she makes a decision whether to invest in health by obtaining prescribed or recommended drugs (D_t), conditional on having been prescribed a drug (P_t).[14] Thus, the unconditional probability of drug purchase (D_t) depends on the probability of the drug prescription (P_t):

$$\Pr(D_t = 1 \cup P_t = 1 \mid \mu) = \Pr(P_t = 1 \mid \mu,) * \Pr(D_t = 1 \mid P_t = 1, \mu).$$

The probability of drug prescription P_t is estimated using a logit model:

$$\Pr(P_t = 1 \mid \mu) = \frac{e^{\beta' W_t^P}}{1 + e^{\beta' W_t^P}} \tag{1}$$

where $\beta' W_t^P = \beta_0 + \beta_1 Y_t^E + \beta_2 Y_t^{HH} + \beta_3 H_t + \beta_4' X_t + \beta_5' C_t^P + \beta_6' O_t + \rho^P \mu$

[14] The RLMS asked all surveyed individuals whether they were prescribed or recommended drugs by a health professional in a medical institution in the past 30 days, but only those who answered yes were then asked whether they obtained all, some or none of these drugs.

Explanatory variables in the drug prescription equations include H_t, which is a lagged health state measured at the end of the previous survey round, individual's socio-demographic characteristics (X_t : age, education, living arrangement dummies that combine information on presence of a spouse and an adult child in the household, number of household members in retirement age, working age and less than 18 years old), community characteristics (C_t^P : community average rates for drug discount eligibility and size, drug availability, and medical care utilization: prevention, treatment of health problems and hospitalization rates), interacted regional and time controls (O_t) and unobserved permanent individual heterogeneity (μ).[15]

The decision to obtain all drugs (D_t) is defined as a choice between obtaining [All] versus [Some or None] of the prescribed or recommended drugs. It is estimated using a logit model:

$$\Pr(D_t = 1 \mid P_t = 1, \mu) = \frac{e^{\gamma' W_t^D}}{1 + e^{\gamma' W_t^D}} \tag{2}$$

where $\gamma' W_t^D = \gamma_0 + \gamma_1 Y_t^E + \gamma_2 Y_t^{HH} + \gamma_3 H_t + \gamma_4' X_t + \gamma_5' C_t^D + \gamma_6' O_t + \rho^D \mu$

All explanatory variables are the same in the drug prescription and drug purchase equations except for the community average rate of drug prescription. The average drug prescription rate is excluded from the drug purchase equation (and the health outcome equation). It serves as a proxy for the environment influencing the doctor's prescribing behavior but not the patient's drug compliance decision.[16]

In all equations, the elderly woman's pension income (Y_t^E) enters the equation separately from household income (Y_t^{HH}). Household income already encompasses her pension income as well

[15] An earlier version of the empirical model included time-variant individual unobserved heterogeneity ν_t but I simplified the model because I found that accounting for ν_t did not improve the goodness of fit of my estimations.

[16] All exclusion restrictions are tested for validity.

as all remaining sources of household income. If the unitary model is correct, only the coefficient on household income should be significant. Thus, a statistically significant pension coefficient would imply a rejection of the income pooling hypothesis.[17]

4.2.3. Health Outcome Equation

The dependent variable in the health production function is health outcome. In the theoretical model it corresponds to health stock at the beginning of Period 2. It is measured as self-assessed health measure with two states (bad versus average/good), constructed from five possible answers (very bad, bad, average, good and very good) in the survey

Health production is estimated using a logit model:

$$\Pr(H_{t+1} = 1 \mid \mu) = \frac{e^{\alpha' W^H_{t+1}}}{1 + e^{\alpha' W^H_{t+1}}} \qquad (3)$$

where $\alpha' W^H_{t+1} = \alpha_0 + \alpha_1 Y^E_t + \alpha_2 Y^{HH}_t + \alpha_3 H_t + \alpha^{'}_4 X_t + \alpha_5 P_t + \alpha_6 D_t +$

$$+ \alpha^{'}_7 P_t \times Y^{HH}_t + \alpha_8 D_t \times Y^{HH}_t + \alpha^{'}_9 C^H_t + \alpha^{'}_{10} O_t + \rho^H \mu$$

Health stock in period *(t+1)* is a function of variables in period *t*: income, lagged health, drug prescription, drug purchase choice, drug prescription and purchase interacted with lagged health, demographic variables and regional and time controls. Health stock is also affected by the unobserved individual heterogeneity and thus estimated jointly with the drug prescription and drug purchase equations.

The community average rates of drug discount eligibility and size and for drug availability are excluded from the health outcome equation. They are assumed to affect health only through their effect on the drug prescription probability and drug purchase decisions.

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[17] I test hypotheses derived from the theoretical model by looking at total income effects, which include not only the direct effect described here but also indirect income effects channeled through other sources (lagged health, drug prescription).

4.3.4. Initial Condition Health Outcome Equation

I account for the endogeneity of the initial health stock H_0 by estimating it as a reduced form equation. H_0 is observed by the econometrician in the first year of data collection for each individual and used as an explanatory variable in the second time period.

$$\Pr(H_0 = 1 \mid \mu) = \frac{e^{\lambda' W_0^H}}{1 + e^{\lambda' W_0^H}} \qquad (4)$$

$$\lambda' W_0^H = \lambda_0 + \lambda_1 height_0 + \lambda_2 height_0 \times age_0 + \lambda_3^{'} X_0 + \lambda_4^{'} O_0 + \rho_0^{H_0} \mu$$

Health stock in the initial condition equation is affected by the same unobserved permanent individual heterogeneity affecting the remaining equations. Identification of this initial condition equation is achieved by using two variables, the elderly person's height and height interacted with age, as exclusion restrictions.

4.3. Estimation Strategy: Discrete Factor Approximation Method

The empirical strategy must account for the presence of unobserved individual characteristics that affect the health outcome, the drug prescription probability and the drug purchase decision. The method used to solve the set of equations in this study is the discrete factor random effects approximation method (Heckman and Singer 1984, Mroz and Guilkey 1992, Mroz 1999). [18] It is a semi-parametric approach that provides consistent estimates. Mroz and Guilkey (1992) extended the method to the system of simultaneous equations and showed that it performs as well as two-stage methods and parametric maximum likelihood estimators imposing joint normality if the errors are normal, and performs better if distributional assumptions are incorrect.

The discrete factor approximation method does not impose distributional assumptions on the error terms, but assumes that the unobserved heterogeneity can be approximated by a discrete distribution with a finite number of mass points of support and associated probability weights. In

[18] The model is estimated using a FORTRAN program Leo with permission of Dr. Mroz.

order to get an unconditional likelihood function, the likelihood function conditional on unobserved heterogeneity must be integrated with respect to the distribution of the unobserved heterogeneity. The distribution of heterogeneity is integrated out through a weighted sum of probabilities.

Let's assume that the unobserved permanent heterogeneity μ follows a discrete distribution with *K* points of support, defined as $pr(\mu = \mu_k) = \pi(k)$ for *k*=1, 2, …, *K*. The location of the mass points and the associated probability weights are estimated jointly with other parameters of the model (the first mass point of support is fixed at 0 and the last one is fixed at 1 so only the location of the in-between points are estimated from the data). The number of mass points of support *K* is determined empirically by the researcher by comparing the likelihood, the coefficients on the endogenous variables and the goodness of fit of models with different heterogeneity specifications.

All parameters, including mass points and probability weights are estimated within the maximum likelihood framework. In this model, the full unconditional maximum likelihood function for *N* individuals is calculated by multiplying each n[th] individual's vector of probability weights $\pi(k)$ on K points of support of the distribution of permanent unobserved heterogeneity μ (line 1) with the individual's contribution to the likelihood function at the initial time period (line 2) and the individual's contribution to the likelihood function at the remaining time periods *t* =2 through T (lines 3, 4, 5).

$$
\begin{aligned}
L_n = \prod_{n=1}^{N} & \left\{ \sum_{k=1}^{K} \pi(k) \right. \\
& \times \left\{ pr(H_0 = 0 \mid \mu_k)^{1-H_{n0}} * (1 - pr(H_0 = 0 \mid \mu_k))^{H_{n0}} \right\} \\
& \times \prod_{t=2}^{T_n} \left\{ pr(P_t = 0 \mid \mu_k)^{1-P_{nt}} \right. \\
& \times \left[(1 - pr(P_t = 0 \mid \mu_k)) \times pr(D_t = 0 \mid \mu_k)^{1-D_{nt}} \times (1 - pr(D_t = 0 \mid \mu_k)^{D_{nt}} \right]^{P_{nt}} \\
& \times pr(H_{t+1} = 0 \mid \mu_k)^{1-H_{n,t+1}} * (1 - pr(H_{t+1} = 0 \mid \mu_k))^{H_{n,t+1}} \Big\} \quad \Big\}
\end{aligned}
$$

The *n*'th individual's contribution to the likelihood function in one of the remaining time periods *t*, conditional on the permanent individual unobserved heterogeneity (μ), is a product of the probabilities of drug prescription (P_t), drug purchase choice (D_t) conditional on drug prescription (P_t) and health (H_{t+1}). T_n is the last observed period.

4.4. Identification

Identification of the system is achieved through present and lagged exogenous variables, present and lagged i.i.d. error terms (i.e., restrictions on the covariance matrix), exclusion restrictions in the initial condition equation, exclusion restrictions in the drug prescription and drug purchase equations, and the nonlinear functional form of all equations (logits).

Endogenous drug purchase D_t, drug prescription P_t and health stock H_t are estimated as functions of both endogenous and exogenous right-hand side variables:

$$D_t = D(Y_t^E, Y_t^{HH}, H_t, X_t, C_t^D, O_t, \mu, u_t^D)$$

$$P_t = P(Y_t^E, Y_t^{HH} t, H_t, X_t, C_t^P, O_t, \mu, u_t^P)$$

$$H_{t+1} = H(Y_t^E, Y_t^{HH}, H_t, X_t, P_t, D_t, C_t^H O_t, \mu, u_t^H)$$

All endogenous variables on the right-hand side can be expressed in terms of lagged exogenous and endogenous variables, for which in turn we can substitute lagged exogenous variables and i.i.d. errors. The path of lagged exogenous variables and i.i.d. errors that generates the variation necessary for the model identification begins in period *t*=1 where the initial condition equations for health stock is identified through two variables excluded from the remaining equations (height and height*age).

Exclusion restrictions in individual equations should be highly correlated with the corresponding outcome variables, but have no direct effect on outcome variables in equations from which they are excluded. Height and height interacted with age are proxies for early childhood health. They are used as instruments in the initial condition equation and are excluded from all time-t equations. The average drug prescription rate proxies the doctor's propensity to prescribe drugs and is used as an instrument in the drug prescription equation; it is excluded from the drug purchase and health equations. Community average rates for drug discount eligibility and size and availability of drugs in pharmacies are included in the drug prescription and drug purchase equations, but are excluded from the health outcome equations.

4.5. Alternative Estimation Strategies

I estimate the drug prescription, drug purchase and health outcome equations using alternative methods in order to better understand how modeling unobserved heterogeneity in the preferred, jointly estimated model changes the coefficients. Models described in Sections 4.5.2 and 4.5.3 address endogeneity of drug prescription and drug purchase in the health outcome equation. The model in Section 4.5.3 also addresses the selection bias associated with modeling drug purchase. The alternative models, as opposed to the preferred, jointly estimated model, do not control for the endogeneity of health. Instead, they treat lagged health as an exogenous regressor, which may lead to biased estimates if lagged health is correlated with unobserved characteristics.

4.5.1. Exogenous Model – No Correction of the Unobserved Heterogeneity Bias

This model does not attempt to correct for any source of unobserved heterogeneity. Each equation is estimated separately. Errors are assumed to be uncorrelated across equations. Drug prescription and drug purchase enter the health outcome equation as exogenous explanatory variables.

4.5.2. Instrumental Variables Method with the First-Stage Modeled as a Two-Part Model – Partial Correction of the Unobserved Heterogeneity Bias

In this model I treat drug prescription and drug purchase as endogenous explanatory variables in the health outcome equation and use the instrumental variables approach to correct for this endogeneity. I generate predicted values of drug prescription and drug purchase using the drug prescription and drug purchase equations. The predicted values then enter the health outcome equation as explanatory variables instead of the observed values. I use the linear probability model in the 2nd stage. [19]

The first stage, in which I estimate drug prescription and drug purchase, is treated as a two-part model. A two-part model assumes that error terms in the two equations are independent. This assumption could be considered feasible in my study because the decisions to prescribe/recommend drugs and obtain drugs are made sequentially by different entities, a doctor and a patient. Some of the same unobserved variables influence both the drug prescription and the drug purchase decisions, such as unobserved health dimensions and patient's attitude to health and health care institutions (patient had to seek out medical care to be prescribed drugs), but the correlation of errors in the two equations may be small. If this correlation is small then a two-part model could be an appropriate method.

4.5.3. Instrumental Variables Method with the First-Stage Modeled as a Sample Selection Model – Partial Correction of the Unobserved Heterogeneity Bias

As in Section 4.5.2., I use the instrumental variables approach to estimate the health outcome, with predicted values of drug prescription and drug purchase entering the health outcome equation as

[19] I report the conditional standard errors as reported by Stata and do not bootstrap the standard errors. In their discussion of the two-step probit regression, Bollen, Guilkey and Morz. (1995) note that when a predicted value of the endogenous regressor is included in the estimation of the 2nd equation, the Monte Carlo evidence does not suggest that computed adjusted standard errors are more effective than the conditional standard errors in large finite samples.

regressors instead of their observed values. But the first stage, in which I generate the predictions of drug prescription and drug purchase, is now treated as a sample selection model instead of a two-part model.

The sample selection model assumes that the errors between the drug purchase and drug prescription equations are correlated. This assumption implies that many of the same unobserved characteristics affect both the likelihood of the drug prescription and the patient's decision to purchase drugs. People with worse unobserved health, a higher unobserved propensity to trust the doctor's judgment and those who value their health more on the margin are more likely to seek out medical care and thus be prescribed drugs as well as adhere to the doctors' advice to buy drugs than those with opposite characteristics. Further, due to the specifics of the drug prescription rules in Russia, people with unobserved worse health are probably overrepresented in the drug purchase equation because those people who qualify to receive discounts and tend to be sicker must go back to doctors' office every 30 days to get a prescription refill while those people who do not qualify for discounts - and tend to be healthier - can keep buying their drugs over the counter for years without seeking out doctors' advice.

Because both the drug prescription and drug purchase equations have binary outcomes I use the Heckman probit estimation (Heckprob in Stata), which is a censored probit, to estimate the selection model. The identification restriction in the selection equation is the average community prescription rate. This variable is highly correlated with the drug prescription, and not correlated with the elderly's decision to purchase drugs. This instrument was tested as part of the preferred, jointly estimated method and passed the identification exclusion test (using the discrete factor analysis model with unobserved heterogeneity parameters).

The use of the selection model in my study has its limitations. The selection model performs well if the portion of the sample in the outcome equation is large. This is not so in my dataset where only approximately 30 percent of elderly individuals were prescribed drugs. 70 percent of my sample is thus censored and the outcome equation estimates are based on thirty percent of the sample. Further, the selection equation does not have a large explanatory power.

CHAPTER 5

DATA

5.1. Dataset

The dataset used in this study is the Russia Longitudinal Monitoring Survey (RLMS) Phase II.[20] The survey gathers comprehensive information on income, health and medical care, both at the individual and household levels, and local infrastructure at the community level. Household information is obtained from the household respondent and the individual-level data are collected from each household member by trained interviewers. Household members can provide answers on behalf of children and those unable to answer.

RLMS is based on a nationally representative sample collected at 160 sites across the Russian Federation, which are assigned to 65 primary sampling units and 8 regions. Each year approximately 4,000 households and between 8,700 and 10,000 individuals within these households are interviewed. The survey does not follow individuals or households who move out from the surveyed dwelling, but instead begins to interview any new families or individuals who move in the surveyed dwellings. A unique identification number is assigned to each household and individual making it possible to link them across multiple rounds.

This study creates a panel of observations using seven survey rounds conducted in Nov.-Dec. 1994 (Round 5), Oct.-Dec. 1995 (Round 6), Oct.-Dec. 1996 (Round 7), Oct.1998-Jan.1999 (Round 8), Sept.-Dec. 2000 (Round 9), Sept.-Dec. 2001 (Round 10) and Sept.-Dec. 2002 (Round 11).

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[20] The RLMS has been created and collected through a collaborative effort of the Carolina Population Center at UNC Chapel Hill and the Russian Academies of Sciences and Medical Sciences.

5.2. Sample Determination

The sample used in this study consists of women who met the age requirement to receive pension, which is 55 years of age and up, and reported receiving pension at the time of the survey.

In rounds 5 through 11 the RLMS collected a total of 17,013 person-year observations for men and women satisfying the age requirement for receiving pension. 262 person-year observations were dropped for individuals who were not receiving pension at the time of the interview and thus were not asked whether they received pension in the past 30 days.[21] An additional 73 observations were dropped because of missing dependent variable data on health evaluation, drug prescription or drug purchase. Because the analysis focuses on the dynamic behavior, I then dropped individuals without the minimum of two consecutive observations and any observations that followed a skipped survey period.[22] I dropped 5 individuals with missing height in all person-year observations.

The sample at this point consisted of 3,405 individuals with 14,655 person-year observations. In order to test the household income pooling hypothesis more than one potential source of income in the household is needed. I therefore eliminated observations for 676 elderly individuals who lived alone or were the only adult in the household.

The relationship between income and health should be studied separately for women and men because of different minimum age requirements for receiving pension as well as different health deterioration paths, as is evidenced for example in the WHO 2004 data on life expectancies at birth, which were 59 years for men and 72 years for women.[23] I thus dropped all men and created a sample

[21] These 262 observations represent individuals who were not receiving pension at all. The reason is unknown – a possible reason is that they may not qualify to receive pension because they are foreigners or did not satisfy the service requirement. The sample does include individuals who reported receiving a pension (i.e. qualified for pension) but did not receive a payment in the past 30 days (pension arrear problem) and those who received a payment in the past 30 days but did not report the pension payment value (missing variables problem).

[22] For example, if an individual participated in Rounds 6, 7, 9, 10 but skipped Round 8, I keep only observations from Rounds 6 and 7 and delete his observations from Rounds 9 and 10.

[23] World Health Organization, http://www.who.int/countries/rus/en/ .

for women only. My final sample of women used in all empirical work in this study consists of 1782 women with 7,283 person-year observations.

In Table 5.1 I report the number of observations in the final sample across individual survey rounds, broken down between the first-time (initial condition) observations and time-t observations. For over 50 percent of women in this sample, the initial observation is from the RLMS Round 5 conducted in 1994. New individuals that were added to the sample in later time periods included women who just reached the minimum age requirement (55) to receive pension, women who moved into the surveyed dwellings and women who did not live consecutively with other adults in previous survey rounds. Table 5.2 reports the number of observations per individual.

Table 5.1: Observations per Survey Round

	Total Number of Observations (IC and time t)	Initial Condition (First Time) Observations	Time-t Observations
1. RLMS Round 5 (1994)	976	976	0
2. RLMS Round 6 (1995)	1122	146	976
3. RLMS Round 7 (1996)	1093	129	964
4. RLMS Round 8 (1998)	1031	165	866
5. RLMS Round 9 (2000)	1010	158	852
6. RLMS Round J (2001)	1091	208	883
7. RLMS Round K (2002)	960	0	960
Total	7283	1792	5501

Table 5.2: Observations per Individual

	Number of Individuals
2 observations	498
3 observations	369
4 observations	246
5 observations	153
6 observations	127
7 observations	371
Total	1782

I replaced inconsistent or missing values for the gender and education explanatory variables with the mode of the variable calculated from all rounds the individual participated in the survey. I replaced missing values for pension income and household income variables with a zero, and created a missing variable indicator set to a 1 for observations with missing values. 5.7 % of household income data in the final sample is missing across all periods (Table 5.6). Household income measure used in this study was constructed by the RLMS by adding up individually reported incomes of household members and is missing if one of the household members did not answer the survey questions.

In the mid 1990s, the Russian government fell behind in pension payments (and wages). The pension arrears problem culminated in 1996. Although the RLMS added direct questions about pension arrears only in later rounds, we could interpret the individuals' response of not having received their pension in the past 30 days as a presence of pension arrears (as opposed to the response that they did receive pension but not disclosing the pension value). In such case the pension arrears would explain 95 percent of the missing pension values across all rounds. The coefficient on the missing variable indicator should be statistically insignificant if income is missing randomly. Because of its role as a proxy for pension arrears, in this study there may be a difference in the behavior of people with and without the missing pension if the elderly with pension arrears lowered their consumption or if the government delayed pension payments to the elderly in some systematic way correlated with their health. No consistent differences between the subsamples with and without missing pension stand out in the descriptive Table 5.3.

Table 5.3: Observations with and without Missing Pension (Pension Arrears)

Missing pension	YES						NO					
	1995	**1996**	**1998**	**2000**	**2001**	**2002**	**1995**	**1996**	**1998**	**2000**	**2001**	**2002**
Drugs prescribed	0.25	0.25	0.32	0.30	0.44	0.42	0.30	0.31	0.28	0.30	0.30	0.30
All drugs Obtained	0.50	0.74	0.61	0.83	0.63	1	0.69	0.70	0.63	0.72	0.84	0.80
Health good or average	0.46	0.55	0.58	0.60	0.44	0.63	0.54	0.54	0.53	0.55	0.58	0.58
Lagged health	0.51	0.54	0.66	0.45	0.36	0.63	0.55	0.57	0.58	0.56	0.58	0.60
Age	66.8	66.4	67.3	69.8	68.7	67.1	66.9	67.6	67.7	68.1	68.4	68.3
Education up to 7 years	0.51	0.39	0.36	0.35	0.40	0.21	0.40	0.36	0.34	0.31	0.29	0.24
Education 8 yrs up to HS	0.25	0.29	0.26	0.35	0.16	0.37	0.25	0.26	0.28	0.29	0.29	0.27
Education complete HS	0.21	0.23	0.24	0.25	0.36	0.42	0.24	0.26	0.27	0.29	0.29	0.32
Education University	0.03	0.09	0.14	0.05	0.08	0.00	0.11	0.13	0.11	0.12	0.13	0.16
Married	0.60	0.65	0.60	0.45	0.56	0.42	0.63	0.61	0.60	0.61	0.57	0.57
Number of household members	2.87	3.15	3.29	3.00	2.92	2.84	3.08	3.01	2.96	3.01	3.01	3.01
Observations	*89*	*330*	*121*	*20*	*25*	*19*	*887*	*634*	*745*	*832*	*858*	*941*
Percent	*9.1*	*34.2*	*14.0*	*2.3*	*2.8*	*2.0*						

Note: All values are percentages.

5.3. Variable Definitions and Descriptive Statistics

5.3.1. Outcome Variables: Health, Drug Prescription and Drug Purchase

<u>Health Outcome</u>

Defining and measuring health stock is challenging because of the multifaceted dimensions of health and measurement errors. Schultz (2001) notes that there is no consensus on how to conceptualize and measure an individual's health status. Health scientists have used health indicators such as self-assessed health, activities of daily living (ADL) indexes, anthropometric measures (body mass index, height), self-reported morbidity measures, morbidity measures from administrative files, and mortality. The RLMS gathers several potential candidates for health status. Data collected directly from individuals provides information on self-assessed health, the extent of functional limitations, several chronic diseases and health problems incurred in the previous month. Weight and height and memory are measured by the interviewer. Mortality, defined as death since the previous survey round, is reported by the main household survey respondent.

This study uses self-assessed health as a proxy of health stock. Self-assessed health is a subjective and potentially noisy measure – it is unclear against what benchmark various elderly compare their health, and perception of average health can also be influenced by conditioning experiences of the individual. On the other hand, it describes the overall health of the individual and reflects the individual's perception of how important various aspects of her health-related wellbeing are. Deaton and Paxson (1998) use it as a single measure of health in their study of income and health relationship. They note that it reflects information individuals have about their health that is unobserved by physicians, and that it correlates with mortality. In the sample used in this study, elderly women with bad self-assessed health had a higher prevalence of chronic diseases and more problems with activities of daily living (Table 5.4).

Table 5.4: Summary Statistics: Illness Prevalence and ADL problems in Self-assessed Health Groups

	Good or Average Health	**Bad Health**
Ever diagnosed with diabetes or increased sugar in the blood	0.07	0.17
Ever experienced pain in your rib cage	0.65	0.84
Ever diagnosed with a myocardial infarction	0.03	0.09
Ever diagnosed with stroke (blood hemorrhage in the brain)	0.02	0.07
Diagnosed with anemia in the last 12 months	0.03	0.06
Problems with Activities of Daily Living		
(Scale 1-5; 1 =not at all difficult; 5 =cannot do it):		
Walk about a kilometer	2.22	3.66
Walk about 200 meters	1.61	2.70
Walk across the room	1.23	2.07
Sit for two hours	1.62	2.36
Stand up after sitting for an extended period	1.86	2.70
Get up from a bed unassisted	1.24	1.96
Climb one flight of stairs without resting	1.65	2.87
Lift and carry abt 5 kg (a sack of vegetables)	1.91	3.16
Squat, crouch or kneel	2.64	3.87
Take a shower or bath unassisted	1.26	2.23
Eat unassisted	1.01	1.26
Dress unassisted	1.07	1.60
Comb your hair unassisted	1.05	1.40
Use the toilet unassisted	1.04	1.50

Note: Values across all periods are recorded.

The RLMS asks the respondents to evaluate their health in the following way: "Tell me, please, how would you evaluate your health?" The respondent chooses between (1) very good, (2) good, (3) average, not good but not bad, (4) bad, (5) very bad. Very few elderly women think highly of their health: across all time periods in this study, only 0.2 percent considered their health to be very good and an additional 3.5 percent good. About 51 percent of the elderly women assessed their health as average, 35 percent bad, and 10 percent very bad. Per-period distribution of self-assessed health is reported in Table 5.5.

In this study I use a dichotomous self-assessed health outcome variable, in which I merge categories (1), (2) and (3) to represent “good” or “average” health, and I merge categories (4) and (5) to represent “bad” health.[24] There has been an upward trend in the sample in the reported self-assessed health (Table 5.5). In 2002, 58.3 percent of women evaluated their health as good or average, up from 53.5 percent of women in 1995.

Drug Prescription

Drug prescription is a dichotomous variable constructed from the survey question “Tell me, please, in the last 30 days did a physician or some other specialist at a medical institution – hospital, polyclinic – write a prescription or advise you to take some kind of medicine?” The variable name ‘drug prescription’ is used throughout this study, but it stands both for drug prescription and drug recommendation. At the time of the study, many drugs typically prescribed in the US needed to be only ‘recommended’ by Russian doctors (e.g. scribbled on a piece of paper), including antibiotics, but the prescription was not required for filling the drug in the pharmacy. An official doctor prescription was required by pharmacists only for dispensing of opiates and drugs eligible for government discounts.

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[24] I considered employing alternative measures of health stock in the empirical model, such as measures of functional status and chronic disease. Per Schultz (2001) measures of limitations in performing activities of daily living (ADL) appear to approximate health states among elderly and reduce bias in measuring health of people with lower socio-economic status. The ADL scale that is used to assess the difficulty of performing everyday tasks, such as bathing, dressing, using the toilet, eating and transferring, was introduced by Katz (1963). I created a similar index using the RLMS data and the Russian context that incorporates responses on help needed with bathing, dressing, eating, using toilet, walking across a room, and climbing stairs. I then used the index to create an ADL dummy that singles out physically impaired elderly from the rest of the elderly. In each of the surveyed years, close to 20 percent of the sample found it at least somewhat difficult to do one or more of these activities. I chose not to use this measure in this study because it was not collected in 2001.

I also created but did not use a chronic disease dummy that equals one if the individual was ever diagnosed with diabetes, increased sugar in blood, myocardial infarction, or a stroke (blood hemorrhage in the brain). The RLMS includes information on the year of the diagnosis, which leads to another potential definition based on the diagnosis in the last calendar year. The last potential health stock measure, used by Jensen and Kaspar (2003), is a dummy measuring chest pain, which indicates potential heart problems. The dummy equals to one if the persons has experienced strong pains in the chest, lasting half an hour or more, in the last 12 months.

On average, about 30 percent of women in the sample were prescribed or recommended drugs in years 1995 to 2002 (Table 5.5).

Table 5.5: Summary Statistics: Outcome Variables

	1994 Round 5	**1995** Round 6	**1996** Round 7	**1998** Round 8	**2000** Round 9	**2001** Round J	**2002** Round K
Outcome Variables							
Health good or average at the end of period	Na	53.5	53.9	53.5	55.2	57.5	58.3
Drugs prescribed or recommended	Na	29.1	28.5	28.9	30.3	30.5	29.8
Sample Size	*0*	*976*	*964*	*866*	*852*	*883*	*960*
All drugs obtained (conditional on drugs being prescribed)	Na	67.6	71.3	62.8	72.5	82.9	80.4
Sample Size	*0*	*284*	*275*	*250*	*258*	*269*	*286*
Survey Responses Used to Construct Dichotomous Outcome Variables Above:							
Health Outcome:							
Very good or good		3.7	4.3	3.7	3.5	2.7	3.6
Average		49.8	49.7	49.8	51.6	54.8	54.5
Bad		38.4	35.9	37.2	33.5	33.6	32.9
Very bad		8.1	10.2	9.3	11.4	8.8	8.7
Drug Purchase:							
All Drugs Purchased		67.6	71.3	62.8	72.5	82.9	80.4
Some Drugs Purchased		9.9	13.1	18.0	9.7	5.2	4.9
No Drugs Purchased		22.5	15.6	19.2	17.8	11.9	14.7

Note: All values are percentages, reported for time t equations.

Drug Purchase

If the respondent answered yes to having drugs prescribed or recommended to her, she was then asked several questions about drug purchasing behavior. I used two survey questions: “Were you able to find or buy some of these medicines?” and ”Tell, me please, were there any medicines prescribed or recommended for you in the last 30 days that you were not able to find or buy?” to construct the measure of access to drugs used in this study. “Drug purchase” is a dichotomous variable reflecting the decision between obtaining all versus not all medicines. It is possible to create a variable with three categories for “none” vs. “some” vs. “all” drugs purchased or obtained, but it is unclear how to interpret the meaning of the response of not being able to buy any versus at least some of the drugs if we don’t know how many drugs were prescribed.

The probability of purchase of all prescribed drugs fluctuated during the studied period (Table 5.5). It was lowest in 1998 (62.8 percent) during the financial crisis. Other than 1998, the probability of purchasing all drugs increased every time period from 67.6 percent in 1995 to 82.9 in 2001 and then fell slightly to 80.4 percent in 2002.

5.3.2. Policy Variables: Income

Pension income used in this study is reported in the RLMS by each individual as “pension received in the past 30 days.”

The RLMS provides two measures of total household income. One is the total household income reported by the main household respondent in the household questionnaire. The error margin on the household respondent’s estimate of “what was the monetary income of your entire family in the last 30 days?” could be large, making it more likely to accept the null hypotheses 1 and 3 in Section 3 that income does not improve access to health investment or lead to better health. To mitigate this measurement error I use a more precise measure constructed by the RLMS by adding labor income, pension income and unemployment benefits reported by individual household members and additional household-level income from other government transfers, home production, gifts and such obtained from the main household respondent. I also employed different definitions of non-labor income, but these did not make a difference in estimation.

Income measures used are the real values with the base month December 2000.[25] Both real pension income and real total household income fell from its largest values (rubles 1,132.78 and 4,467.59 respectively) in 1994 by 42 percent during the 1998 financial crisis marked by hyperinflation, but rebounded in 2000 and 2001 to rubles 1051.14 (pension) and 3652.17 (total household income).

It is likely that income does not have a linear effect on health and health investment. The effect of the rubles in the first quartile of income might be larger than the effect of rubles in the last quartile of income. Thus, I explore both linear and non-linear measures of income, which include the logarithmic transformation where the effect of each additional dollar decreases as income increases, and spline functions that allow us to estimate a different marginal effect of the additional ruble within each quartile.

Pension arrears plagued 35 percent of the elderly during the 1996 pension crisis and might have had repercussions for access to health care and health outcomes. Pension arrears are an example of unanticipated transitory change in income, and are represented in the model by a dummy standing for their presence. People who did not receive pension but knew that this condition is temporary and the government would pay them with delay, may not alter their consumption behavior (lifecycle theory).

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[25] In December 2000 (Round 9), the exchange rate was approximately 28 rubles per dollar. The exchange rate was approximately 30 rubles per dollar in late 2001 (Round 10), and as of 12/27/07 approximately 25 rubles per dollar.

Table 5.6: Summary Statistics: Individual and Household Explanatory Variables

	1995	1996	1998	2000	2001	2002
Sample Size	*976*	*964*	*866*	*852*	*883*	*960*
Policy Variables:						
Pension Income	813.13	681.33	616.45	770.48	954.37	1091.68
Standard Error	*[379.46]*	*[547.63]*	*[305.63]*	*[248.85]*	*[367.94]*	*[390.11]*
Pension Arrears /missing	9.1%	34.2%	14.0%	2.3%	2.8%	2.0%
If pension not missing	894.7164	1035.967	716.5656	789.01	982.17	1113.72
Standard Error	*[292.19]*	*[297.10]*	*[191.73]*	*[220.87]*	*[334.64]*	*[361.50]*
Total Household Income	3724.41	3609.35	2981.11	3561.32	4298.96	4903.30
Standard Error	*[3007.33]*	*[3908.84]*	*[2567.59]*	*[3425.87]*	*[3933.59]*	*[5041.61]*
Missing Household Inc.	4.8%	5.9%	5.1%	6.3%	5.5%	6.6%
Individual and Household Characteristics:						
Sample Size	*976*	*964*	*866*	*852*	*883*	*960*
Age	66.93	67.19	67.63	68.13	68.37	68.24
Standard Error	*[8.73]*	*[8.66]*	*[8.26]*	*[7.90]*	*[8.14]*	*[8.12]*
Lagged health	54.9%	55.8%	59.2%	55.9%	57.4%	60.2%
Education up to 7 years	40.8%	36.8%	33.8%	30.8%	29.4%	24.4%
Education 8 yrs up to HS	25.0%	27.2%	27.8%	28.9%	28.5%	26.9%
Education HS completed	23.9%	24.6%	26.7%	28.5%	29.2%	32.5%
Education University co.	10.3%	11.4%	11.7%	11.9%	12.8%	15.9%
Living arrangement:						
Spouse, no other adults	37.4%	36.8%	38.5%	39.4%	38.3%	36.8%
Spouse, adults, no child	3.6%	4.0%	4.3%	2.8%	2.8%	3.2%
Spouse & adult child	17.9%	17.7%	14.8%	15.3%	14.0%	15.1%
No spouse, adults, no child	7.6%	7.7%	6.7%	5.8%	7.0%	8.0%
No spouse & adult child	29.9%	30.2%	33.4%	34.0%	35.7%	35.4%

Note: All values other than pension and household income measures and age are percentage, reported for time-t equations.

5.3.3. Other Explanatory Variables

Individual and Household Variables

The education proxy was constructed using several RLMS questions on grades completed and diplomas received.[26] In 1994, 45 percent of participants had less than 7 years of education, 24 percent completed 7 or more years of school but did not graduate from high school, 21 percent graduated from high school but did not receive a university level diploma, and 10 percent received a university level diploma. Average education attainment increased over time.

Age effects are measured using the squared transformation (age squared) because it allows the effect of one-year increase in age to change as a person gets older. The effect of age on is not likely to remain the same as we get older. Increasing age might have a positive effect on drug purchase in the fifties, even out later, and maybe even become negative in very old age.

Height is the most common and readily available indicator or early childhood and adolescent health. Adult person's height is affected by the environment and nutrition of mother and child and conditions during adolescent growth (Schultz 2001). This relationship might be more applicable in developing than developed countries. Russian women in this sample were born prior to 1945, and thus were very likely to have spent their early childhood facing serious resource constraints – whether it was during WWII or the years beforehand. While height does not substantially change between 25 and 55 years of age, it is negatively correlated with the elderly people's age. Introduction of an interaction variable that measures the effect of height for different age eliminates the bias caused by this correlation.[27]

[26] The Soviet definition of primary school changed several times over time, and until 1956 the required education was 7 years. The spike at seven years of education suggests that for elderly Russians in the sample 7 years of education was a milestone. The number of people with 7 grades completed was almost five times higher than the number of people with 6 grades, and three times higher than the number of people with 8 grades.

[27] Use of interaction terms of height with ethnicity and place of birth is unfeasible because these variables have many missing values in the RLMS.

The household level control variables reflect the household living arrangement: whether the individual lives with a spouse, an adult biological child, or other adults, as well as the number of household members in the retired category and working category, and children under 18.

Table 5.7: Summary Statistics: Community Level Explanatory Variables

		1995	**1996**	**1998**	**2000**	**2001**	**2002**
Sample Size		*976*	*964*	*866*	*852*	*883*	*960*
	Instrument						
Average drug prescription rate	Eq. 2	29.2	29.2	28.9	28.9	28.7	29.1
Average drug discount eligibility rate	Eq.2,3	59.1	56.0	50.4	43.1	44.7	46.2
Average drug discount size rate	Eq.2,3	84.5	85.9	81.9	79.5	80.8	82.3
Average Rate drugs not in pharmacy – fixed, elderly	Eq.2,3	51.5	51.6	51.7	51.4	51.5	51.3
Average Rate drugs not in pharmacy – time-specific, responses from all adults	Eq.2,3	66.1	49.2	38.8	27.2	27.1	21.7
Average rate of health problems reported		41.9	42.5	41.4	43.0	44.3	43.1
Average rate of medical provider visit to treat health problem		40.5	40.7	40.8	37.3	28.7	30.4
Average prevention visit rate		14.7	13.2	12.8	14.8	17.7	15.5
Average hospitalization rate		4.9	4.8	5.0	5.1	5.3	4.9

Note: All values are percentages.

Community Variables

The characteristics of the community in which the individual lives may also affect medical care use, access to drugs and health outcomes. To proxy the community characteristics I created time-specific, community-level average rates for 38 primary sampling units that include: (1) average hospitalization rate, (2) average prevention rate, (3) average rate of health problems reported, (4) average rate of a medical provider visit in case of a health problem, (5) average drug prescription rate, (6) average drug discount eligibility rate, (7) average drug discount size rate, (8) two definitions of the average rate at which the reason "drugs not available in pharmacy" was given by patients who did not obtain all drugs. The algorithms excluded the observation for which the average rates were computed. The rates were based on the sample of the elderly used in this study and on the sample of all individuals living in the community, who are older than 18 years.

Community average rates (1) – (4) may be determinants of all outcome variables: drug prescription, drug purchasing behavior and health state because they reflect overall health of population in the community (may be influenced e.g. by local pollution level), accessibility of local medical care institutions and local medical care-seeking conventions. For example, areas with high average hospitalizations, prevention and treatment visit rates might signal that the area has many or easily accessible hospitals and polyclinics. That in turn could mean that people are more likely to seek out medical care with less severe health problems than people in areas with low utilization rates and then doctors are less likely to prescribe drugs. Of course, one could argue the other way: high utilization rates might be an indication of an unhealthy population. Either way, the market characteristics proxied by average regional rates would affect the doctor's propensity to prescribe drugs.

The probability of drug prescription may depend also on the conventions in the area where the doctor (or other medical worker) works. I use the average community-level rate of drug prescriptions (5) as a proxy for the doctors' environment. Community average rates (6) – (8) may affect the drug prescribing and drug purchasing behaviors. The elderly women would be more likely to obtain drugs in areas with generous local drug discount eligibility rules and fewer drug supply problems in pharmacies. According to Minkevich (1998) Russian doctors consider drug price and availability when prescribing or recommending drugs to patients. To capture such effect on doctors' propensity to prescribe drugs, I use the average community-level rate of reported "drugs not available in pharmacy," average drug discount eligibility and discount size rate as explanatory variables also in the drug prescription.

Time dummies, regional dummies and interactions of time and region further help control for time-varying community-level changes, such as changes in local infrastructure and prices, which affect household resources, health and health drug utilization outcome variables. Stillman & Thomas (2006) used region-time interactions but found that their inclusion did not affect the main results.

CHAPTER 6

RESULTS

The preferred model jointly estimates the empirical equations describing drug prescription, drug purchase and health status. It accounts for the existence of unobserved individual permanent characteristics correlated across all equations by modeling unobserved individual heterogeneity.

In Section 6.1, I describe selected coefficients and marginal effects in individual equations of the preferred jointly estimated model and compare them to estimates obtained using alternative, exogenous-health methods: (i) an exogenous model that treats all variables as exogenous, (ii) an instrumental variable model with a selection model used in the first stage, and (iii) an instrumental variable model with a two-part model used in the first stage. I then investigate if the estimates change when alternative income definitions (spline functions) and income interactions with lagged health and living arrangement are used.

The preferred model's structural character allows us to model dynamic behavior at the level of the set of equations in addition to evaluating results at the individual equation level, and makes it possible to find and simulate total income effects that affect the drug purchasing behavior and the health production simultaneously. Such simulations can provide useful insights for policy makers. In Section 6.2, I report results at the set of equations level. I discuss the goodness of fit of the preferred model, test theoretical hypotheses, and simulate effects of policy changes similar to the 2005 Russian law, which replaced drug discount subsidies with cash transfers directed to pensioners.

6.1. Equation-Specific Coefficient Estimates in the Preferred Model

6.1.1. Drug Prescription Equation

Drug prescription is a dichotomous variable - equal to one if the woman reported having any drugs prescribed or recommend to her in a medical institution in 30 days prior to the survey interview; otherwise it is equal to zero. This variable reflects not only the physician's decision to prescribe or recommend drugs, but also the patient's decision whether or not to seek care in a medical institution.

In the preferred, jointly estimated model with log income measures I find little evidence of income effects. A pension increase of 100 rubles increases the probability of having drugs prescribed by 0.07 percent, or a pension increase of 400 rubles (which was between 35 and 50 percent of the average real pension income during the studied period) increases the drug prescription probability by 0.28 percent (Table 6.1). The effect of the household income is statistically insignificant and even smaller in magnitude than the pension effect.

The lack of evidence of income effects of any substantial magnitude on the drug prescription behavior could be explained by the presence of the universal health care system in Russia. Russians were officially entitled to free medical care, in which case income should not be expected to play a role in the patient's decision to seek medical care. But in the real world of Russian health care, it could. Policlinics and hospitals suffered from insufficient government funding and some reacted by instituting out-of-pocket fees for services such as X-ray tests, in spite of the official free care guarantee. A lot of attention has also been paid to under-the-table, unofficial payments to doctors in Russia. This study's results imply that if such out-of-pocket official and unofficial out-of-pocket payments for medical care were present, they made very little difference in the elderly women's likelihood of having drugs prescribed.

Table 6.1: Marginal Effects – Drug Prescription and Drug Purchase Equations: (i) Exogenous Model, (ii) Selection Model, (iii) Preferred, Jointly Estimated Model

	Drug Prescription			**Drug Purchase**		
	(i) Exogen.	**(ii) Selection**	**(iii) Joint**	**(i) Exogen.**	**(ii) Selection**	**(iii) Joint**
Pension (10 ruble increase both in pension and household income)	**.00073****	**.00073****	**.00072****	.00016	.00003	.00013
Household Income (10 ruble increase, but no pension increase)	-.00026	-.00026	-.00015	.00045	.00033	.00037
Lagged health status (rated as average or better)	**-.173****	**-.172****	**.0465**	**.0791****	.0791	-.00007
Age (increase by 1 year)	**.0036****	**.0036****	**.0081****	.0033	.0030	.0011
Education – university degree				**-.0926***	-.0744	**-.0634***
Community prescription rate (10% increase)	**.0941****	**.0953****	**.0708****			
Community drug eligibility rate (10% increase)	.0008	.0008	-.0007	**.0223****	**.0251****	**.0187****
Community drug unavailability rate (10% increase)	.0112	.0113	**.0123***	**-.0218***	-.0203	**-.0256****
Community health problem reported rate (10% increase)	**-.0298****	**-.0301****	-.0166	**.0319***	.0364	.0223
Community doctor visit rate to treat health problem (10% increase)	-.0175	-.0176	-.0057	**.0540***	**.0609****	**.0440****
Community preventive visit rate (10% increase)	**.0546****	**.0541****	**.0433****	**-.1106****	-.1035	**-.0970****
Rural Area vs. Urban Area		.0107	.0147		.0141	.0317

Notes: *** significant at 5 percent level*
** significant at 10 percent level*

If the small pension income effect is driven by the patient's decision to seek out medical care, then the lack of any significant household income effect suggests that households do not pool resources in allocation decisions with regard to medical care consumption.

The lack of income effects on drug prescription could also occur if Russian doctors do not induce demand for drugs for higher-income patients who are more able to pay nor withhold drug prescriptions from those with low income. The statistically significant, albeit very small, positive pension income effect might indicate that doctors are able to assess the patient's pension income and are slightly more likely to prescribe drugs to patients with higher pension.

Income effects found in the preferred, jointly estimated model are similar to income effects found in the exogenous model and the selection model (Table 6.1), which implies that unobserved characteristics modeled in the preferred model are not correlated with income, contingent on having drugs prescribed. The model with a log pension income spline function indicates that the pension income effect is non-linear: only an additional ruble in the lowest (first) and highest (fourth) pension income quartiles increases the probability of drug prescription (Table A.2).[28]

The positive effect of the missing pension income dummy is intriguing because this variable mostly reflects the presence of pension arrears (Table A.1). People who did not receive a pension check from the government the month of the survey were more likely to seek out medical care and have drugs prescribed - maybe the stress of not having any current income flow and the uncertainty surrounding the next payment could have made them more susceptible to onsets of illnesses.

(Table 6.1). In the two models with exogenous lagged health, the probability of having drugs prescribed was 17 percentage points higher for a person with bad lagged self-assessed health compared to a person with good or average lagged health. Once we treat lagged health as an endogenous variable in the preferred model, affected by the same unobserved permanent characteristics of the individual as her drug prescription and drug purchasing behavior, it leads to a

[28] Interactions of income with lagged health and two living arrangement dummies (being married and living with an adult child) were statistically insignificant. Adding them to the model did not change the main results (Table A.2).

4.6 percent increase in the probability of having drugs prescribed or recommended while the effect of unobserved heterogeneity is negative. The effect attributed to lagged health in alternative models becomes captured by unobserved characteristics variable in the preferred model. These unobserved characteristics likely include positive attitudes to health care and perhaps a more accurate approximation of the individual's health. The sum of the observed self-assessed health and unobserved health characteristics effects is negative.

Three proxies for characteristics of the community in which the elderly woman lives affect the drug prescription probability.[29] The community's average drug prescription rate serves as a proxy for the doctor's propensity to prescribe drugs, and as such it reflects the effect of the local geographic area conventions – both patient expectations and institutional influences on the doctor (for example, though marketing of pharmaceutical companies). The average drug prescription rate increases the probability of drug prescription by 7 percentage points, indicating that doctors are influenced by the conventions in their area (Table 6.1). The probability of drug prescription is also higher in communities with higher average rates of preventive visits and in communities where individuals were more likely to report not being able to find prescribed drugs in pharmacies (Table 6.1). Out of demographic characteristics, age increases the likelihood of drug prescription (Table 6.1).

6.1.2. Drug Purchase Equation

Drug Purchase is a dichotomous variable equal to one if the individual reported obtaining all drugs prescribed or recommend to her, and equal to zero if she did not obtain at least some of the drugs in 30 days prior to the survey. Only those individuals who were prescribed or recommended to obtain drugs were included in the subsample asked questions about drug purchasing behavior.

Neither household income nor pension income had a statistically significant direct effect on the elderly women's decision to obtain drugs, conditional on having drugs prescribed. This lack of

[29] Computation of all average community rates were individual-specific and excluded the answer of the individual.

income effects was present also in the alternative selection and exogenous models (Table 6.1). [30] When log household income is replaced with a log household income spline function in the preferred model, we can detect a positive, statistically significant effect (10 percent level) of the additional ruble in the 4th quartile (Table A.4). This suggests that the decision to purchase drugs is influenced by income only at high income levels - maybe because people with highest income levels are treated differently by doctors and get more types of drugs prescribed or recommended to them and are more critical of doctors' choices and thus more selective about whether to obtain all drugs.

Considering the fact that from 29 percent (1994) to 67 percent (2002) of the surveyed elderly women who did not obtain all drugs often reported not having enough money as one of the reasons – (similar to the range from 20 percent of urban Russians in 1994 to 66 percent in 2000 in the WHO 2003 report on Russia, based on the RLMS data), the lack of income effect in this study is an unexpected finding. The lack of the relationship between income and the decision to obtain all prescribed or recommended drugs may indicate that drugs are viewed as a necessity by the participants of this survey. It may be that a lower income would lead people to forgo purchases of expensive foods such as meat or discretionary items such as clothing rather than drugs that were prescribed or recommended to them. It is also possible that this study cannot capture the income effect well enough because the drug purchase outcome variable represents a very heterogeneous group of drugs associated with a wide range of prices as well as different perceptions of necessity and thus different income elasticity.

Using the RLMS data I cannot address the research questions using only one specific, homogenous drug. However, I can postulate that drugs prescribed or recommended to elderly women in the RLMS are quite likely to be for relatively serious conditions and thus likely to be perceived as a

[30] In exploratory exogenous and selection model estimations, in which I used a larger sample of women (before deleting those who lived alone and had non-consecutive observations), I found statistically significant income effects, but of very small magnitude. The magnitude was similar to the magnitude of the effects in the exogenous and selection models reported in Table 6.1 (albeit in Table 6.1 these effects were found to be statistically insignificant).

necessity, which could partially explain the very inelastic demand with respect to income. Russians did not need a prescription in order to purchase the majority of over-the-counter drugs, including antibiotics, and thus had less incentive to seek out medical care and visit a doctor. Those individuals who reported having drugs prescribed or recommended in a medical institution must have sought out medical care, which would be more likely if they had a relatively serious health condition and viewed drugs as a necessity. This notion is supported by the fact that individuals with most serious co-morbidities were granted the "invalid" status which qualified them for drug discounts but required them to obtain a prescription refill for discounted drugs. Consequently, people with bad self-assessed health who are more likely to have chronic diseases and ADL problems (Table 5.4) are heavily represented in the subsample of people with drugs prescribed, contributing to the estimated lack of income effects.

In models treating lagged health as exogenous, people in average or good lagged self-assessed health were 7.9 percent more likely to purchase prescribed drugs than those in bad health (Table 6.1). Once we endogenize health in the preferred model, then this effect becomes insignificant, and is picked up by the positive coefficient on individual unobserved heterogeneity. This implies that there is no systematic difference between the drug purchasing decisions of the elderly women with average/good self-assessed lagged health versus bad health, contingent on having drugs recommended or prescribed by a physician. The unobserved health and attitudes capture the difference in drug purchasing behavior. I explore the different behavior of groups with good versus bad health in more depth in Section 6.4 of this chapter.

Women with a university education were less likely to purchase all prescribed drugs than women with lower education, maybe because they felt more knowledgeable about their health condition and able to second guess the doctor's decision. The study found no effect of age on drug purchasing behavior.

Several community characteristics seem to be important determinants of the drug purchasing behavior (Table 6.1). Women were more likely to obtain all drugs if they lived in an area with more generous drug discount eligibility rules (i.e. higher percentage of people in their area qualified for discounts) and in an area where people were more likely to visit a doctor if they had a health problem. Women were less likely to obtain all drugs if they lived in an area with more substantial drug supply problems in pharmacies (proxied by the percentage of people who reported not being able to find a drug in the pharmacy) or in an area with a higher rate of preventive visits.

6.1.3. Health Outcome Equation

The health status outcome is a dichotomous variable based on the individual’s self assessment of health; it is equal to one if the individual reported an average or good health at the end of the period and equal to zero if the individual reported being in bad health.

Both pension income and household income have positive direct effects on the health outcome (Tables A.7 and A.8). The magnitudes of these effects are small, in line with the very small income-health gradient found in Russia by past research (Lokhsin & Ravallion 2008). A 100 ruble increase in household income that is not caused by an increase in the elderly woman’s pension leads to a 0.05 percentage point increase in the elderly woman’s probability of being in good health. A 100 ruble increase in the elderly woman’s pension income leads to a 0.1 percentage point increase in her probability of being in good health. The fact that pension income has a stronger marginal effect on health than household income suggests that the source of income matters in the household allocation of resources regarding health production of individual members. An increase in pension income may increase the elderly woman’s bargaining power within the household and allow her to allocate more resources to improve her health.

Direct income effects are comparable across the preferred jointly estimated model, instrumental variables models and the exogenous model (Table 6.2). The extension of the model with log household income spline function indicates that the effects of household income are nonlinear. The positive effect of a ruble increase in the first quartile has the highest magnitude (Table A.4).

Lagged health is a crucial predictor of the elderly woman's current health. In models that treat lagged health as exogenous, those with good or average lagged health are 41 percent more likely to be in good or average health also at the end of the period. Once we endogenize lagged health in the preferred model, this effect falls to 24 percent. Unobserved heterogeneity modeled in the preferred model thus is responsible for part of the effect attributed to lagged health in models treating lagged health as exogenous. The difference between the effects of lagged health in the preferred model and models treating it as exogenous highlights the importance of endogenizing health.

Receiving a drug prescription is a predictor of worse health outcome for women with good or average lagged health but it does not have an effect on women already in bad lagged health. While the decision to obtain all drugs did not affect health of elderly women with bad lagged health, it did make a difference in the health outcome of women with good or average lagged health. If a healthy woman obtained all prescribed or recommended drugs then her descent into the bad health state was slowed down by 10 percentage points, compared to a healthy woman who did not purchase all prescribed or recommended drugs. This implies that drug therapy may be effective in health maintenance of the elderly people.

The likelihood of maintaining good or average health is higher for women with higher education and falls with age (Table 6.2). The likelihood of maintaining good or average health also falls if the elderly woman lives in a rural area or in an area with high rates of reported health problems. It increases if the elderly woman lives in an area with a high rate of doctor visits to treat a health problem or in an area with a high preventive visit rate. These results indicate that policies that improve access to medical care may be effective in improving or maintaining health of the elderly women in Russia.

Table 6.2: Marginal Effects – Health Status Equation: (i) Exogenous Model, (ii) Two-part Model, (iii) Selection Model, (iv) Preferred, Jointly Estimated Model

	Health Status			
	Models with Exogenous Health			**Preferred**
	(i) Exogenous	**(ii) Two-Part**	**(iii) Selection**	**(iv) Joint**
Pension (10 ruble increase both in pension and household income)	**.0011****	**.0011****	**.0011****	**.0010****
Household Income (10 ruble increase, but no pension increase)	**.0005****	**.0005****	**.0005****	**.0005****
Lagged health status (Average or better = 1)	**.4093****	**.4179****	**.4069****	**.2417****
Drug prescribed/recommended (i.e. bad health get a rx)	**-.2096****	**-.2094****	-.0918	-.0379
Drugs obtained (i.e. bad health get a rx and take all vs. bad health who did not get rx)	-.1863	-.1694	-.0615	-.0666
Drug prescribed* good lagged health (i.e. good health get a rx vs good health who did not get rx)	**-.3526***	**-.5239****	**-.3829***	**-.1720****
Dugs obtained* good lagged health (i.e. good health get a rx and take all vs. good lagged health who did not get rx)	**-.2002****	**-.1368****	**-.1964****	**-.0738****
Age (increase by 1 year)	**-.0111****	**-.0117*****	**-.0121****	**-.0148****
Education – high school vs lowest	**.0334****	**.0356****	**.0325***	**.0383****
Education – university degree vs lowest	**.0522****	**.0682****	**.0730****	**.0771****
Community health problem reported rate (10% increase)	**-.0237****	**-.0267****	**-.0291****	**-.0275****
Community doctor visit rate to treat health problem (10% increase)	**.0178****	**.0178***	.0124	**.0158***
Community preventive visit rate (10% increase)	**.0278***	**.0321****	.0376	**.0267***
Lives in rural area	**-.0319****	**-.0323****	**-.0338****	**-.0290****

** significant at 5 percent level
 * significant at 10 percent level

6.1.4. Unobserved Heterogeneity Factor Loadings in Individual Equations

The differences between the effects of lagged health, drug prescription and drug purchase estimated in the preferred model and the alternative models are evidence that modeling unobserved heterogeneity is important. In the preferred model, unobserved heterogeneity had a positive effect on drug purchase and the health outcome and a negative effect on drug prescription. Based on these results, the components of unobserved permanent individual characteristics most likely driving the unobserved heterogeneity variable effect are some positive health dimensions, risk aversion to bad health and positive attitudes toward the health care system.

6.2. Choosing the Preferred Model and the Goodness of Fit

In order to find he preferred model using the discrete factor analysis method, I jointly estimated the set of equations for different specifications of permanent and time-variant unobserved heterogeneity, trying out between one and four mass points for both unobserved heterogeneity distributions. I compared the goodness of fit of models with alternative mass point specifications and assessed the accompanying changes in the endogenous coefficients and the log-likelihood using the likelihood ratio test.

I chose the model with four permanent heterogeneity mass points and without any time-variant heterogeneity as the preferred model because adding more mass points did not improve log likelihood significantly. The distribution of the permanent unobserved heterogeneity in the preferred model is summarized in Table A.5. The placement of the normalized mass points was estimated to be at 0.0, 0.43, 0.70 and 1.0. On this 0 to 1 scale, the elderly woman's unobserved characteristics would be represented by the value 0.0 with a 3 percent probability, 0.43 with a 25 percent probability, 0.7 with a 52 percent probability and 1.0 with a 20 percent probability. I found that adding the time-variant individual unobserved heterogeneity did not lead to an improvement of the model's goodness of fit or the likelihood. Therefore I did not include the time-variant heterogeneity in the preferred model specification.

To assess the goodness of fit, I compared means of the predicted outcome variables to means of the outcome variables observed in real life. To generate the predicted outcomes, I used coefficients estimated in the preferred model, which included both coefficients for the observed explanatory variables and coefficients (loadings) for the unobserved permanent heterogeneity as well as the mass points representing permanent unobserved heterogeneity, also estimated in the model. In computation of the predicted probabilities, unobserved heterogeneity coefficients were multiplied by randomly assigned mass points. I drew random errors to assign the predicted outcome value of zero or one: if the random error was larger than the predicted probability then the simulated binary outcome was assigned the value one; otherwise the simulated outcome was zero. In each period, I replaced observed endogenous explanatory variables with the last period's predicted outcomes and then computed a new set of predicted outcomes for the current period. I generated 100 predicted outcomes per observation, each with a different set of random errors used to assign outcomes from the computed probabilities.

In Tables 6.3 I report the goodness of fit of models with different income specifications summarized across all periods. The preferred model predicts the probability of having drugs prescribed or recommended very close to its observed mean. The prediction that 30.3 percent of the sample is prescribed or assigned drugs is close to the drug probability mean of 29.5 percent observed in real life. Similarly, the prediction that on average 54.7 percent of the sample is in average or good health at the end of the period is close to the observed 56.3 percent of the sample reporting to be in good or average health.

The predicted probability of all drugs being purchased is on average 4.9 percent higher than the drug purchase probability observed in real life. This discrepancy is likely caused by inaccuracies in the selection of the group for which drug purchase is simulated. In the simulation of drug prescription (selection equation), the group that is predicted to have drugs prescribed has a better lagged health on average than the group that had drugs prescribed in real life. This accuracy issue could be mitigated in the future by an extended model that incorporates medical care demand equations, and in which the outcome variables in these new equations are added as explanatory variables in the drug prescription equation.

The goodness of fit was similar for models with different definitions of income. The model with the pension spline function had a slightly better fit than the basic model with log pension income: the predicted outcomes were 0.24 percent closer to observed average drug prescription, 0.13 percent closer to the observed average drug purchase, and 0.57 percent closer to the observed average health outcome. However, this was not a major improvement in the fit of the model. I chose to use the basic model as the preferred model because of the ease of interpretation of its results.

The exclusion restrictions in individual equations of the preferred model were tested for validity. All instruments were significant or jointly significant in the equations where they belong. The likelihood ratio test was conducted and confirmed that the instruments were not statistically significant predictors in equations from which they were excluded.[31]

[31] In this likelihood ratio test the preferred model is considered the restricted model, and the model in which the instruments are added to all equations is considered the unrestricted model.

Table 6.3: Goodness of Fit Summary: (i) Basic Model, (ii) Extension with Income Interactions, (iii) Household Income Spline Function, (iv) Pension Spline Function

	Preferred Model (Basic)		**Extension: Income Interactions**		**Extension: Household Income Spline Function**		**Extension: Pension Spline Function**	
ALL OBSERVATIONS (first time period - initial condition)								
IC health	**0.584**							
Predicted	0.583	*-0.03%*	0.589	*0.55%*	0.581	*-0.27%*	0.589	*0.57%*
ALL OBSERVATIONS (time period = 2, 3, 4, 5, 6 or 7)								
Drugs Prescribed	**0.295**							
Predicted	0.303	*0.81%*	0.300	*0.50%*	0.301	*0.64%*	0.297	*0.26%*
Drugs Obtained	**0.731**							
Predicted	0.780	*4.90%*	0.783	*5.29%*	0.780	*4.96%*	0.778	*4.77%*
Health Outcome	**0.553**							
Predicted	0.547	*-0.67%*	0.545	*-0.81%*	0.550	*-0.33*	0.552	*-0.10%*

Note: All estimations are for Het 4-1, no normalization of time-invariant coefficients. 100 reps in simulations.

6.3. Results at the Set of Equations Level

6.3.1. Simulations - Testing Income Effect Hypotheses

To summarize and paraphrase my formal hypotheses, Hypothesis 1 tests whether income affects drug purchase of the elderly woman; Hypothesis 2 tests whether the household pools its resources and thus the elderly woman's drug purchasing behavior depends only on total household income, regardless of her contribution to it; Hypothesis 3 tests whether income affects the elderly woman's health; and Hypothesis 4 tests whether the household pools its resources in production of the elderly woman's health.

Income affects the elderly woman's decision to purchase drugs directly by increasing her ability to pay for drugs, but also indirectly by having influenced both her lagged health in the previous period and her probability of having drugs prescribed or recommended to her. The coefficients on household income and pension income in the drug purchase equation can be used to compute the direct marginal effect of income. However, to test the hypotheses derived from the theoretical model, we should look at the total income effects, which include both direct and indirect components. To do so, we must look at the preferred model's results at the set of equations level.

I use simulations 1, 2, 3 and 4 (referred to as S1, S2, S3 and S4 below) to test the four hypotheses postulated in the theoretical model. The reported results are point estimates (Table 6.4). In simulations S1 and S3, I increase household income without increasing the elderly woman's pension income – in other words, the source of the increase in household income is a household member other than the elderly woman. In simulations S2 and S4 I increase both pension income and household income by the same amount – here the source of the increase in household income is the elderly woman's pension. In simulations S1 and S2, the income increase is 100 rubles in each time period. In Simulations S3 and S4, the income increase is 400 rubles in each time period.

Table 6.4: Simulation Results: Hypothesis Testing

	Base Model	**Simulation 1: Increase household income by 100 rubles every time period**		**Simulation 2: Increase pension income by 100 rubles every time period**		**Simulation 3: Increase household income by 400 rubles every time period**		**Simulation 4: Increase pension income by 400 rubles every time period**	
			Change from Base Model		**Change from Base Model**		**Change from Base Model**		**Change from Base Model**
Drugs Prescribed	**0.295**								
Predicted	0.303	0.303	*-0.04%*	0.311	*0.81%*	0.302	*-0.09%*	0.331	*2.82%*
Drugs Obtained	**0.731**								
Predicted	0.780	0.781	*0.11%*	0.778	*-0.11%*	0.782	*0.21%*	0.774	*-0.56%*
Health Outcome	**0.553**								
Predicted	0.547	0.549	*0.21%*	0.553	*0.64%*	0.551	*0.48%*	0.566	*1.95%*

Notes: Average values across all time t (2 through 7) periods are reported. Coefficients from the preferred model and 100 replications of each observation are used.

Increasing the elderly woman's pension income by 100 rubles (S1) has a negative total effect of a very small magnitude on the probability of obtaining all prescribed/recommended drugs (-0.12 percent on average each period). Increasing household income without increasing pension income (S2) has a positive effect of similar magnitude on the probability that all drugs are purchased (0.11 percent). These total income effects reflect both the statistically insignificant direct effects of income on drug purchase as well as several indirect income effects channeled through (1) the effect of lagged health on drug purchase (statistically insignificant) which in turn is influenced by the effect of income in the health production function (positive and significant), and (2) the effect of income on drug prescription (positive, statistically significant for pension income and insignificant for household income) which in turn is influenced also by the lagged health (positive, statistically significant) and thus the effect of income in the health production function (positive and significant). Both the direct and the main indirect effects (1) and (2) through which additional indirect effects are channeled are statistically insignificant and of small magnitude (except for the pension effect on drug prescription). I cannot reject the null Hypothesis 1 that income does not affect drug purchasing behavior. I reject the null Hypothesis 2 that households pool resources.

Increasing the household income via increasing the elderly woman's pension by 100 rubles increases the elderly woman's probability of being in good or average health by 0.65 percent (a 400 ruble pension income increase leads to a 2 percent increase in the probability of good or average health). Increasing the household income caused by an increase of some other household member's income leads to a smaller effect on health: a 100 ruble household income increase leads to a 0.21 percent improvement in health (a 400 ruble household income increases the elderly woman's probability of being in good or average health by 0.5 percent). Because the direct and main indirect income effects are statistically significant, albeit of small magnitude, I reject the null Hypothesis 3 that income does not affect the health outcome. I reject the null Hypothesis 4 that households pool resources because an increase in the pension income has a four times larger positive marginal effect on the elderly woman's health than an increase in some other household member's income.

The model allows us to see the dynamic character of the positive income effect on health. In the Table 6.5 I report the increase in the probability of good or average health for the sub-sample of elderly women observed in all 7 rounds between 1994 and 2002. During this time, their likelihood of being in good or average health declined as they aged, by approximately 10 percentage points. However, an income increase can slow down the descent into bad health, and the positive effect on health would accumulate over time. For example, if the government increased the elderly women's pension income by 400 rubles in each time period, their likelihood of good or average health would be 2.1 percent higher in the first period and 4.5 percent higher in the seventh period.

Table 6.5: Simulation Results: Per-period Effect of Pension Income Increase on Health

	Predicted Health Outcome		Total Per-period Effect of Pension Income Increase on the Likelihood of Good or Average Health Outcome	
	Baseline Preferred Model	Simulation S4 (400 ruble increase in pension income each time period)	Percentage points (S4 minus Base)	Percent Change
Round 2 (1995)	0.588	0.600	0.012	2.058
Round 3 (1996)	0.574	0.591	0.017	3.031
Round 4 (1998)	0.524	0.545	0.021	4.097
Round 5 (2000)	0.507	0.530	0.023	4.581
Round 6 (2001)	0.520	0.537	0.017	3.279
Round 7 (2002)	0.487	0.509	0.022	4.520

6.3.2 Simulations - Government Policies

I next use estimates from the preferred model to simulate the effects of potential policy changes. The ability to predict the total effects of a policy is a useful advantage of the joint estimation method that corrects for endogeneity of health; such policy simulations could not be made using only direct effects estimated in each equation separately. In January 2005, a new Russian law went into effect, replacing in-kind drug discounts with cash transfers to the elderly.[32] I simulate what would happen to the drug purchase behavior and the health of our sample if discounts were eliminated from all regions during all periods and replaced by a cash grant in all periods. I report results (point estimates) from these selected policy simulations in Table 6.6.

I first look at the effect of eliminating drug discounts without any cash compensation in Simulation S5. I set the average community rates of drug discount eligibility and drug discount size equal to zero across all regions and time periods. The elimination of discounts seems to have a profound effect on the behavior of the elderly women: it lowers their probability of obtaining prescribed/recommended drugs by 14.4 percentage points. The effect on their health is also negative but less dramatic: it lowers the probability of being in good health by 0.75 percentage points.

[32] The law officially went into effect in January 2005, but individual regions have been dragging their feet implementing it.

In S6 and S7 I simulate the new law. I eliminate drug discounts and at the same time generate a cash transfer to the elderly by increasing their pension income each period by 400 rubles (S6) and, less generously but more realistically, by 200 rubles (S7). In the case of a 400 ruble increase in pension income, the new law would lead to a 16.2 percentage point decrease in the elderly women's probability of obtaining the prescribed/recommended drugs and at the same time increase their probability of the good health outcome by 1.18 percentage points. In the case of a 200 ruble increase in the pension income, the law would decrease the probability of obtaining drugs by 14.8 percentage points and increase the probability of good or average health by 0.4 percentage points.

Table 6.6: Simulation Results: Policies

	Base Model	**Simulation 5: Eliminate discounts**		**Simulation 6: Increase pension income by 400 rubles AND eliminate discounts**		**Simulation 7: Increase pension income by 200 rubles AND eliminate discounts**		**Simulation 8: Increase regional discount eligibility and size to 100%**	
			Change from Base Model		**Change from Base Model**		**Change from Base Model**		**Change from Base Model**
Drugs Prescribed	**0.295**								
Predicted	0.303	0.360	*5.66%*	0.390	*8.69%*	0.376	*7.28%*	0.289	*-1.37%*
Drugs Obtained	**0.731**								
Predicted	0.780	0.635	*-14.43%*	0.628	*-15.18%*	0.632	*-14.81%*	0.862	*8.24%*
Health Outcome	**0.553**								
Predicted	0.547	0.539	*-0.76%*	0.558	*1.16%*	0.550	*0.35%*	0.549	*0.23%*

Notes: Average values across all time t (2 through 7) periods are reported. Coefficients from the preferred model and 100 replications of each observation are used.

In simulation S8 I look at the effect of providing free drugs to all elderly as an alternative to cash grants. I set the average community discount eligibility rate equal to one across all regions and time periods, and set the discount size equal to 100 percent of the drug price. I find that providing free drugs to elderly women would increase their probability of obtaining the prescribed/recommended drugs by 8.21 percent but increase the probability of being in good or average health only by 0.23 percent, less than S6 and S7.

Comparing the effects of an in-kind drug subsidy policy (S8) to the effects of unrestricted cash grants (S6 and S7), it seems that unrestricted cash grants would lead to a lower demand for drugs (and thus lower drug expenditures) and a bigger improvement in the health outcome of the elderly women than in-kind drug subsidies would. An income increase that is not restricted to drug use can increase an individual's utility by allowing her to allocate resources to alternative health investments, such as better diet, better living conditions, or activities that help reduce stress. The unrestricted cash grant thus seems to be a better option regardless of whether the Russian government's goal is to improve the health outcome of the elderly or lower the country's drug expenditures. This conclusion, however, is based on simulation of very short-term effects on the health outcome. The effect of the above policies may be different if the health outcome is measured at a later point of time instead of the end of the survey round, as is done in this study. To assess whether replacing in-kind drug discounts with cash transfers is cost effective in the long run we would have to consider the effects of lowered drug use on longer-term health and any the related forms of medical care considered substitutes for drugs.

6.4. Extension: Comparing Behavior of Groups with Different Lagged Health

The preferred model controls for lagged health, but other than that it assumes that income effects as well as any other socio-demographic, institutional, regional and time effects are the same for all elderly women, regardless of their lagged health status. However, we might expect women with bad self-reported lagged health to face more serious illnesses and different institutional conventions and constraints, such as drug discount eligibility and drug availability in pharmacies, than women with good or average lagged health. Thus the effects of many of socio-demographic and institutional factors on the behavior and the health outcome of the two groups may differ. I partially address this issue by creating an extended version of the preferred model that includes interactions of lagged health with pension and household income, which however produces results close to the preferred model (Tables A.2, A.3 and A.4).

I thus proceed to expand the preferred, four-equation model to a six-equation model, in which I estimate the drug prescription and the drug purchase decisions using different equations for the groups of women with bad lagged health (relatively less healthy women) and women with good or average lagged health (relatively more healthy women).[33] I find different pension effects for the two groups in the drug prescription equation, different pension effects in the drug prescription equation, and different effects of community characteristics in both equations (Tables A.6, A.7, and A.8).

In the drug prescription equation, the pension effect and pension arrears effect is stronger for women with good lagged health than women with bad lagged health. Further, women with good lagged health were more likely to have drugs prescribed if they lived in areas with high average drug prescription rates, low incidence of reported health problems and high average preventive visit rates; these community characteristics had no effect on drug prescription of women with bad lagged health. Overall, it appears that community factors have an influence on the drug prescribing pattern when it

[33] I estimate the six-equation model for three definitions of income: logarithmic transformations of household income and pension income, a spline function for log pension income, and a spline function for log household income.

comes to relatively more healthy patients, but prescription patterns for less healthy patients are not as much community driven.

In the drug purchase equation, income effects continue to be insignificant for both groups. The interesting finding is that the average discount eligibility discount rate has a positive effect on the drug purchasing behavior of women with bad lagged health, but no effect on women with good lagged health. This can be expected because only individuals with serious comorbidities can qualify for the "invalid" status in Russia and be eligible for drug discounts. The local prevalence of discounts is irrelevant to healthy women who are not likely to qualify. The likelihood of obtaining all drugs decreased for the healthier group of women if they had a university education, lived in areas with higher rates of reported problems of drug availability in pharmacies or in areas with higher average rates of doctor visits to treat a health problem; their likelihood of obtaining all drugs was also lower in several regions.

The effect of income and lagged health is slightly lower in the 6-equation system than the 4-equation system. The effects of socio-demographic and community characteristics on health are comparable in the two models.

CHAPTER 7

CONCLUSION

7.1. Discussion

In this study I address the relationship between income, drug purchase decision and health of elderly Russian women. I do not find evidence of household income or pension income affecting elderly women's decisions to obtain drugs, but I find that income has a modest positive effect on the health outcome. An increase in the elderly woman's pension income has a stronger positive effect on her health than an increase in household income that originated from some other source. Thus, contrary to the unitary model, the relative control over resources in the household does seem to matter in Russia and influence the resource allocation among household members. The policy implication of the limits to household pooling of resources is that if the government's goal is to improve elderly women's health or welfare then transfer interventions targeting their personal income, such as pension, would be most effective.

This study finds that obtaining all prescribed or recommended drugs lowers the probability of descending into bad health by 10 percentage points for women with good or average self-assessed lagged health who were prescribed drugs. This finding implies that drug therapy can be an effective form of disease management. This is an important result in the world marked by skepticism regarding whether drug therapy is effective in maintaining health of the elderly. However, findings of the policy simulations in Section 6.3.2 suggest that increases in income (pension income cash transfers) may be a more effective way to increase the likelihood of good health outcome than increasing drug consumption via in-kind drug subsidies (drug discounts directed to the elderly). This finding should be generalized across borders with caution: a relatively lower effect of the drug-targeted costs on health compared to direct income effects could be more characteristic of countries with more serious resource constraints, such as Russia, than more wealthy countries, such as the U.S.

The estimates from the preferred structural model that included unobserved heterogeneity differed from the estimates obtained from the exogenous and two-stage (IV, Heckprob) models. The difference indicates that permanent individual unobserved heterogeneity plays a role in determining the outcomes and should be accounted for in the estimation. The statistically significant factor loadings on unobserved heterogeneity in individual equations imply that elderly women who were more likely to obtain prescribed or recommended drugs were also more likely to be in good health and less likely to have drugs prescribed.

7.2. Limitations and Future Research

The preferred, jointly estimated model used to analyze the relationship between income, drug purchasing behavior and the health outcome in this study is concise and intended to serve as a foundation for future research. An expanded future version should consider including additional equations for attrition and death, and the decisions to seek out medical care to treat health problems and to receive preventive care, which affect the probability of having drugs prescribed. Any such expansions of the set of equations would require finding new valid exclusion restrictions, which is not a trivial task.

A limitation of this study arises also from the definitions and measurements of the outcome variables. The study distinguishes only between two states of the health outcome: (1) good or average health and (2) bad health. This measure was created from a five-point-scale self-assessed health survey answers. I explored using different measures of health, such as self-assessed health rated on a five-point scale and the index for problems with activities of daily living (ADL). The ADL index could not be used in the studied period because questions needed to construct it were not included in one of the survey rounds. However, a research project of a different period may avoid this problem and include ADL and a health outcome measure.

Health benefits of many chronic disease management drugs may become evident only after several years of use. This study may thus underestimate the overall benefits of drugs because it looks at the health outcome at the end of the calendar year during which drug purchasing decisions were made. Measuring the health outcome several years after assessing the drug purchasing behavior could quite likely lead to finding stronger effects of drug purchasing behavior on health outcome. Since the construction of this study's dataset, five more RLMS rounds were conducted, making it more possible to analyze long run effects of drugs in future research.

The RLMS collects data on the decision to obtain drugs in general, but does not distinguish between different types of drugs. The drug purchase variable that encompasses all types of drugs in its definition makes it more difficult to capture income effects. While this study found little evidence of income effects on the decision to obtain drugs in general, such effects may be visible in studies focused on one specific type of drugs.

Because many drugs were available over-the-counter without any prescription and did not require a contact with a physician, in this study some drug users may have incorrectly been selected into the group of people with no drug prescription and thus no drug use. An inclusion of drug users in the no-drug-use group would lead to an underestimation of the effect of drugs on health.

The choice of economic resource measures may also be further explored. The end of 1998 income data comes from the period of hyperinflation in Russia, and using monthly deflators to compute real income values may not generate sufficiently accurate measures. The use of household income and pension income measures in this study allows making straightforward assessment of the pooling hypothesis, which is one of the study's objectives. It may be interesting, however, to investigate replacing household income measure with household assets or expenditures (consumption) to proxy for household resources. For example, current expenditures are usually considered to be more accurately collected than household income and may better reflect current and long term well-being.

This study uses current income measures to estimate income effects. Replacing current income measures with proxies for permanent income could lead to finding larger income effects. Duflo (2001) and Behrman et al (1990) argue that studies of income effects should focus on permanent unexpected rather than current income changes, and Stillman (2002) also distinguishes between transitory and permanent shocks to income. This distinction has its origin in the life cycle theory, according to which households can transfer resources from one period to another and ride out transitory shocks to resources, or in other words smooth out their consumption. If households weather current income fluctuations then using a transitory definition of income would lead to underreporting of income effects on consumption decisions. One way to tease out the effect of transitory versus permanent pension and household income in this study would be to follow Stillman (2006) and define the permanent income as the average income over all observed rounds and compare its effect to the effect of the transitory income shocks defined as deviations from the permanent income.

Further, household income, pension income and the living arrangement (e.g. living with an adult child) are treated as exogenous explanatory variables in this study, not affected by health of the elderly women. An extension to this research may explore estimating household income and living arrangement simultaneously with the health outcome and health investment behavior, as well as modeling the pension income as an initial condition equation. However, estimating the living arrangement choice using the RLMS is problematic because the survey did not collect data from elderly women on family members not living in the household. Only in one of the rounds used in this survey elderly women were asked if and how many living children they had.

Last but not least, regional differences in medical services, drug prices and drug discount eligibility laws are not always readily transparent in Russia. Federal and state rules exist, but often are not adhered to, sometimes due to the lack of funds. Research studies, such as this one, must be aware of their limitations arising due to these complexities.

APPENDIX A: Estimation Results

Table A.1: Set of Four Equations in the Preferred, Jointly Estimated Model (Coefficients)

	Health Status IC		Drugs Prescribed		Drugs Obtained		Health Status	
Height	0.227**	*[4.128]*						
Height*age	-0.003**	*[-3.952]*						
Log pen income			0.522**	*[3.483]*	-0.153	*[-0.697]*	0.295**	*[2.212]*
Pension miss			3.548**	*[3.479]*	-0.823	*[-0.556]*	2.148**	*[2.379]*
Log household income			-0.030	*[-0.796]*	0.057	*[0.984]*	0.121**	*[3.172]*
Household income miss			-0.255	*[-0.715]*	0.609	*[1.116]*	1.311**	*[3.681]*
Lagged Health			0.305**	*[3.136]*	0.000	*[-0.003]*	1.395**	*[10.180]*
Drug Prescr							-0.216	*[-0.986]*
Drugs Obtained							-0.167	*[-0.722]*
Health*prescr							-0.789**	*[-2.789]*
Health*purchase							0.725**	*[2.350]*
Age	0.373**	*[2.270]*	0.350**	*[5.170]*	-0.050	*[-0.432]*	-0.287**	*[-4.194]*
Agesq	0.00	*[0.435]*	-0.002**	*[-4.602]*	0.000	*[0.511]*	0.001**	*[2.820]*
Lives with spouse, other adults, not own adult child			0.009	*[0.036]*	0.307	*[0.764]*	-0.366	*[-1.517]*
Lives with spouse and own adult child			0.055	*[0.323]*	0.337	*[1.216]*	-0.480**	*[-3.027]*
Lives with other adults, not own child or spouse			-0.273	*[-1.368]*	0.247	*[0.861]*	0.022	*[0.120]*
Lives with own adult child, no spouse			-0.123	*[-0.831]*	-0.202	*[-0.944]*	-0.262*	*[-1.859]*
Number children			-0.099	*[-1.369]*	0.023	*[0.198]*	0.030	*[0.506]*
Number working adults			-0.089	*[-1.287]*	0.120	*[1.052]*	0.099	*[1.583]*
Number retirees			-0.271**	*[-2.424]*	0.071	*[0.402]*	0.153	*[1.472]*
Education 2	0.313*	*[1.664]*	-0.101	*[-0.710]*	0.233	*[1.321]*	0.059	*[0.489]*
Education 3	0.553**	*[2.765]*	-0.044	*[-0.307]*	0.121	*[0.666]*	0.264**	*[2.109]*
Education 4	0.785**	*[3.083]*	-0.078	*[-0.425]*	-0.379*	*[-1.671]*	0.537**	*[3.177]*
Avg Prescr			4.314**	*[4.060]*				
Avg Disc Elig			-0.044	*[-0.116]*	1.268**	*[2.225]*		
Avg Disc Size			-0.004	*[-0.625]*	0.002	*[0.183]*		
Avg No Drug 1			0.010	*[0.022]*	0.849	*[1.270]*		
Avg No Drug 2			0.779*	*[1.843]*	-1.634**	*[-2.336]*		

Table A.1: Set of Four Equations in the Preferred, Jointly Estimated Model (Coefficients) (Continued)

	Health Status IC		Drugs Prescribed		Drugs Obtained		Health Status	
Avg Health Pr	-1.964*	*[-1.907]*	-1.081	*[-1.482]*	1.521	*[1.365]*	-1.918**	*[-2.866]*
Avg DocVisit	-0.447	*[-0.445]*	-0.367	*[-0.531]*	3.124**	*[2.883]*	1.110*	*[1.760]*
Avg Prevention	0.917	*[0.788]*	2.682**	*[2.750]*	-5.715**	*[-3.602]*	1.883*	*[1.956]*
Avg Hospital	6.432	*[1.469]*	2.950	*[1.584]*	-3.160	*[-0.740]*	0.756	*[0.308]*
Region n	-0.289	*[-0.707]*	0.175	*[0.364]*	0.095	*[0.128]*	-0.531	*[-1.092]*
Region c	-0.323	*[-1.123]*	0.406	*[1.244]*	0.331	*[0.558]*	-0.417	*[-1.241]*
Region v	-0.033	*[-0.112]*	-0.166	*[-0.450]*	0.210	*[0.323]*	-0.252	*[-0.717]*
Region u	-0.031	[-0.094]	0.447	*[1.179]*	0.789	*[1.178]*	0.141	*[0.365]*
Region ws	-0.249	[-0.751]	0.955**	*[2.382]*	-0.367	*[-0.558]*	-0.283	*[-0.702]*
Region es	-0.355	[-1.033]	0.147	*[0.346]*	0.338	*[0.495]*	-0.361	*[-0.892]*
Region ca	-0.556*	[-1.671]	0.438	*[1.102]*	0.119	*[0.178]*	-0.403	*[-1.046]*
Rural	-0.084	[-0.509]	0.094	*[0.718]*	0.213	*[1.186]*	-0.202**	*[-1.976]*
1996	0.218	[0.850]	0.563	*[1.459]*	1.258	*[1.617]*	-0.277	*[-0.672]*
1998	0.456*	[1.651]	1.114**	*[2.845]*	0.805	*[0.993]*	-0.263	*[-0.623]*
2000	-0.216	[-0.849]	0.798*	*[1.860]*	-0.181	*[-0.248]*	0.554	*[1.229]*
2001	0.201	[0.798]	1.002**	*[2.243]*	1.345	*[1.509]*	1.273**	*[2.532]*
2002	0.114	[0.406]	0.301	*[0.788]*	0.067	*[0.102]*	0.218	*[0.597]*
TimeXreg_3_2			-0.176	*[-0.288]*	-1.077	*[-1.033]*	0.177	*[0.271]*
TimeXreg_3_3			-0.631	*[-1.407]*	-2.069**	*[-2.429]*	0.342	*[0.705]*
TimeXreg_3_4			0.035	*[0.074]*	-1.542*	*[-1.701]*	0.139	*[0.281]*
TimeXreg_3_5			-0.444	*[-0.871]*	-1.476	*[-1.526]*	-0.042	*[-0.077]*
TimeXreg_3_6			-1.210**	*[-2.315]*	-1.099	*[-1.143]*	1.080*	*[1.904]*
TimeXreg_3_7			-0.482	*[-0.865]*	-1.320	*[-1.354]*	0.399	*[0.689]*
TimeXreg_3_8			-0.890*	*[-1.696]*	-1.335	*[-1.376]*	0.358	*[0.665]*
TimeXreg_4_2			-1.010	*[-1.561]*	-2.121**	*[-1.965]*	0.034	*[0.050]*
TimeXreg_4_3			-0.822*	*[-1.822]*	-1.656*	*[-1.883]*	0.417	*[0.845]*
TimeXreg_4_4			-0.560	*[-1.144]*	-0.771	*[-0.795]*	0.275	*[0.545]*
TimeXreg_4_5			-1.238**	*[-2.359]*	-2.386**	*[-2.385]*	-0.347	*[-0.619]*
TimeXreg_4_6			-1.552**	*[-2.834]*	-1.595	*[-1.585]*	0.380	*[0.660]*
TimeXreg_4_7			-0.249	*[-0.440]*	-2.160**	*[-2.173]*	0.895	*[1.497]*
TimeXreg_4_8			-0.711	*[-1.359]*	-1.952**	*[-1.994]*	0.610	*[1.123]*
TimeXreg_5_2			-0.018	*[-0.027]*	-0.203	*[-0.216]*	-0.675	*[-0.980]*
TimeXreg_5_3			-0.450	*[-0.951]*	-0.136	*[-0.170]*	-0.112	*[-0.215]*
TimeXreg_5_4			-0.070	*[-0.140]*	0.843	*[0.937]*	-0.341	*[-0.643]*
TimeXreg_5_5			-0.686	*[-1.258]*	-0.864	*[-0.957]*	-0.465	*[-0.795]*
TimeXreg_5_6			-1.207**	*[-2.150]*	1.253	*[1.298]*	-0.945	*[-1.577]*
TimeXreg_5_7			-0.385	*[-0.630]*	-0.017	*[-0.017]*	-0.584	*[-0.944]*

Table A.1: Set of Four Equations in the Preferred, Jointly Estimated Model (Coefficients) (Continued)

	Health Status IC		**Drugs Prescribed**		**Drugs Obtained**		**Health Status**	
TimeXreg_5_8			-0.224	*[-0.422]*	0.046	*[0.052]*	0.290	*[0.511]*
TimeXreg_6_2			-0.589	*[-0.900]*	-1.343	*[-1.251]*	-1.259*	*[-1.734]*
TimeXreg_6_3			-1.126**	*[-2.298]*	-0.444	*[-0.464]*	-0.925	*[-1.632]*
TimeXreg_6_4			-0.192	*[-0.378]*	0.867	*[0.825]*	-1.083*	*[-1.899]*
TimeXreg_6_5			-1.241**	*[-2.233]*	-1.012	*[-0.920]*	-1.067*	*[-1.705]*
TimeXreg_6_6			-1.440**	*[-2.573]*	-0.484	*[-0.460]*	-0.174	*[-0.273]*
TimeXreg_6_7			-0.663	*[-1.086]*	-1.060	*[-0.960]*	-1.259*	*[-1.930]*
TimeXreg_6_8			-0.460	*[-0.842]*	-0.332	*[-0.322]*	-0.616	*[-1.016]*
TimeXreg_7_3			0.119	*[0.283]*	0.813	*[1.081]*	0.136	*[0.301]*
TimeXreg_7_4			0.163	*[0.357]*	1.685*	*[1.904]*	0.242	*[0.523]*
TimeXreg_7_5			-0.719	*[-1.398]*	0.380	*[0.389]*	0.013	*[0.025]*
TimeXreg_7_6			-0.955*	*[-1.794]*	1.283	*[1.404]*	-0.296	*[-0.526]*
TimeXreg_7_7			0.302	*[0.529]*	0.178	*[0.185]*	-0.460	*[-0.812]*
TimeXreg_7_8			0.317	*[0.652]*	-0.250	*[-0.314]*	0.376	*[0.750]*
Constant	-32.637**	[-3.407]	-15.256**	*[-5.712]*	0.002	*[0.001]*	6.615**	*[2.526]*
Rhocl (Heterogeneity)	6.532**	[6.596]	-6.250**	*[-7.303]*	2.172**	*[4.395]*	4.833**	*[6.418]*

Table A.2 Drug Prescription Equation: Comparison of Different Income Specifications (Coefficients)

			Time Invariant Heterogeneity - 4 Mass Points							
	No heterogeneity		**Basic Model**		**Income Interactions**		**Log Pension Income Splines**		**Log Household Income Splines**	
Likelihood:	-7769.57		-7552.36		-7547.10		-7548.85		-7541.24	
Log pension	0.491**	*[3.838]*	0.522**	*[3.483]*	0.51566**	*[3.365]*			0.50153**	*[3.307]*
Lpen spline1							1.04599**	*[2.777]*		
Lpen spline2							-0.330	*[-0.514]*		
Lpen spline3							0.541	*[0.750]*		
Lpen spline4							0.947*	*[1.705]*		
Pension miss	3.287**	*[3.789]*	3.548**	*[3.479]*	3.562**	*[3.499]*	6.874**	*[2.819]*	3.389**	*[3.294]*
Health* log pension					0.017	*[0.464]*				
No spouse* log pension					-0.007	*[-0.158]*				
Adult child* log pension					0.007	*[0.173]*				
Log household income	-0.044	*[-1.406]*	-0.030	*[-0.796]*	-0.038	*[-0.811]*	-0.032	*[-0.847]*		
Lhh spline1									-0.065	*[-1.412]*
Lhh spline2									0.202	*[0.576]*
Lhh spline3									-0.039	*[-0.120]*
Lhh spline4									0.058	*[0.313]*
Household inc missing	-0.394	*[-1.354]*	-0.255	*[-0.715]*	-0.263	*[-0.711]*	-0.262	*[-0.742]*	-0.443	*[-1.167]*
Health* log hhinc					0.037	*[1.033]*				
No spouse* loghhinc					0.022	*[0.540]*				
Adult child* loghhinc					-0.041	*[-1.077]*				
Lagged Health	-0.861**	*[-13.343]*	0.305**	*[3.136]*	-0.081	*[-0.251]*	0.309**	*[3.232]*	0.294**	*[2.982]*

Table A.2 Drug Prescription Equation: Comparison of Different Income Specifications (Coefficients) - Continued

			Time Invariant Heterogeneity - 4 Mass Points							
	No heterogeneity		**Basic Model**		**Income Interactions**		**Log Pension Income Splines**		**Log Household Income Splines**	
Age	0.273**	*[5.118]*	0.350**	*[5.170]*	0.349**	*[5.400]*	0.350**	*[5.097]*	0.353**	*[5.090]*
Age sq	-0.002**	*[-4.962]*	-0.002**	*[-4.602]*	-0.002**	*[-4.777]*	-0.002**	*[-4.551]*	-0.002**	*[-4.528]*
Lives with spouse, other adults, not own adult child	-0.035	*[-0.182]*	0.009	*[0.036]*	0.025	*[0.095]*	0.013	*[0.049]*	0.006	*[0.024]*
Lives with spouse and own adult child	-0.010	*[-0.078]*	0.055	*[0.323]*	0.323	*[0.918]*	0.048	*[0.288]*	0.062	*[0.368]*
Lives with other adults, not own child or spouse	-0.248*	*[-1.832]*	-0.273	*[-1.368]*	-0.357	*[-0.894]*	-0.287	*[-1.480]*	-0.266	*[-1.348]*
Lives with own adult child, no spouse	-0.126	*[-1.174]*	-0.123	*[-0.831]*	0.017	*[0.042]*	-0.118	*[-0.798]*	-0.119	*[-0.795]*
Number children	-0.055	*[-1.079]*	-0.099	*[-1.369]*	-0.093	*[-1.258]*	-0.099	*[-1.375]*	-0.104	*[-1.410]*
Number working adults	-0.078	*[-1.489]*	-0.089	*[-1.287]*	-0.088	*[-1.223]*	-0.086	*[-1.253]*	-0.109	*[-1.524]*
Number retirees	-0.143*	*[-1.735]*	-0.271**	*[-2.424]*	-0.264**	*[-2.381]*	-0.269**	*[-2.412]*	-0.293**	*[-2.579]*
Education 2	-0.069	*[-0.814]*	-0.101	*[-0.710]*	-0.111	*[-0.791]*	-0.102	*[-0.735]*	-0.099	*[-0.693]*
Education 3	-0.005	*[-0.056]*	-0.044	*[-0.307]*	-0.045	*[-0.314]*	-0.052	*[-0.361]*	-0.040	*[-0.280]*
Education 4	0.030	*[0.256]*	-0.078	*[-0.425]*	-0.086	*[-0.479]*	-0.086	*[-0.472]*	-0.085	*[-0.464]*
Avg Prescr	4.662**	*[5.004]*	4.314**	*[4.060]*	4.310**	*[3.835]*	4.257**	*[4.026]*	4.368**	*[3.920]*
Avg Disc Elig	0.025	*[0.081]*	-0.045	*[-0.116]*	-0.052	*[-0.136]*	-0.037	*[-0.096]*	-0.087	*[-0.228]*
Avg Disc Size	-0.005	*[-0.941]*	-0.004	*[-0.625]*	-0.004	*[-0.644]*	-0.004	*[-0.671]*	-0.004	*[-0.617]*
Avg No Drug 1	0.216	*[0.562]*	0.010	*[0.022]*	-0.021	*[-0.046]*	0.006	*[0.012]*	0.032	*[0.070]*
Avg No Drug 2	0.565	*[1.249]*	0.779*	*[1.843]*	0.769*	*[1.803]*	0.788*	*[1.856]*	0.777*	*[1.849]*
Avg Health Pr	-1.590**	*[-2.667]*	-1.081	*[-1.482]*	-1.041	*[-1.427]*	-1.086	*[-1.470]*	-1.062	*[-1.416]*
Avg DocVisit	-0.913	*[-1.284]*	-0.367	*[-0.531]*	-0.382	*[-0.546]*	-0.354	*[-0.512]*	-0.363	*[-0.518]*
Avg Prevention	2.709**	*[3.227]*	2.682**	*[2.750]*	2.654**	*[2.735]*	2.659**	*[2.706]*	2.65**	*[2.723]*

Table A.2 Drug Prescription Equation: Comparison of Different Income Specifications (Coefficients) - Continued

			Time Invariant Heterogeneity - 4 Mass Points							
	No heterogeneity		Basic Model		Income Interactions		Log Pension Income Splines		Log Household Income Splines	
Avg Hospital	1.702	*[0.946]*	2.951	*[1.584]*	3.023	*[1.408]*	2.827	*[1.346]*	2.919	*[1.159]*
Rural	0.046	*[0.535]*	0.094	*[0.718]*	0.087	*[0.681]*	0.097	*[0.747]*	0.088	*[0.668]*
1996	0.552	*[1.389]*	0.563	*[1.459]*	0.552	*[1.367]*	0.592	*[1.507]*	0.555	*[1.583]*
1998	0.973**	*[2.347]*	1.114**	*[2.845]*	1.106**	*[2.635]*	1.021**	*[2.470]*	1.129**	*[3.162]*
2000	0.668	*[1.510]*	0.798*	*[1.860]*	0.794*	*[1.731]*	0.795*	*[1.789]*	0.794**	*[2.016]*
2001	0.895**	*[1.972]*	1.002**	*[2.243]*	1.008**	*[2.088]*	0.989**	*[2.151]*	0.988**	*[2.417]*
2002	0.378	*[1.003]*	0.301	*[0.788]*	0.286	*[0.709]*	0.290	*[0.740]*	0.282	*[0.802]*
Constant	-14.232**	*[-6.794]*	-15.255**	*[-5.712]*	-15.06**	*[-6.071]*	-18.579**	*[-5.356]*	-14.955**	*[-5.571]*
Rhocl (Heterogeneity)			-6.249**	*[-7.303]*	-6.236**	*[-7.290]*	-6.231**	*[-7.094]*	-6.316**	*[-7.480]*

Table A.3 Drug Purchase Equation: Comparison of Different Income Specifications (Coefficients)

	No heterogeneity		Basic Model		Income Interactions		Log Pension Income Splines		Log Household Income Splines	
			Time Invariant Heterogeneity - 4 Mass Points							
Likelihood:	-7769.57		-7552.36		-7547.10		-7548.85		-7541.24	
Log pension	-0.157	*[-0.664]*	-0.153	*[-0.697]*	-0.132	*[-0.615]*			-0.260	*[-1.410]*
Lpen spline1							-0.012	*[-0.023]*		
Lpen spline2							-0.304	*[-0.330]*		
Lpen spline3							0.182	*[0.194]*		
Lpen spline4							-0.592	*[-0.741]*		
Pension miss	-0.847	*[-0.531]*	-0.823	*[-0.556]*	-0.782	*[-0.550]*	0.092	*[0.027]*	-1.650	*[-1.330]*
Health* log pension					0.063	*[1.022]*				
No spouse* log pension					-0.037	*[-0.477]*				
Adult child* log pension					-0.054	*[-0.739]*				
Log household income	0.056	*[0.898]*	0.057	*[0.984]*	0.045	*[0.675]*	0.058	*[1.020]*		
Lhh spline1									-0.058	*[-0.805]*
Lhh spline2									0.520	*[0.924]*
Lhh spline3									0.305	*[0.541]*
Lhh spline4									0.769*	*[1.921]*
Household inc missing	0.600	*[0.993]*	0.609	*[1.116]*	0.718	*[1.205]*	0.619	*[1.133]*	-0.002	*[-0.004]*
Health* log hhinc					-0.053	*[-0.850]*				
No spouse* loghhinc					0.085	*[1.191]*				
Adult child* loghhinc					0.002	*[0.036]*				
Lagged Health	0.458**	*[3.476]*	0.000	*[-0.003]*	0.020	*[0.037]*	-0.004	*[-0.025]*	-0.004	*[-0.026]*

Table A.3 Drug Purchase Equation: Comparison of Different Income Specifications (Coefficients) - Continued

	No heterogeneity		Time Invariant Heterogeneity - 4 Mass Points: Basic Model		Income Interactions		Log Pension Income Splines		Log Household Income Splines	
Age	-0.038	*[-0.330]*	-0.050	*[-0.432]*	-0.041	*[-0.371]*	-0.049	*[-0.424]*	-0.048	*[-0.448]*
Agesq	0.000	*[0.515]*	0.000	*[0.511]*	0.000	*[0.455]*	0.000	*[0.507]*	0.000	*[0.562]*
Lives with spouse, other adults, not own adult child	0.223	*[0.561]*	0.307	*[0.764]*	0.302	*[0.746]*	0.302	*[0.751]*	0.348	*[0.857]*
Lives with spouse and own adult child	0.393	*[1.448]*	0.337	*[1.216]*	0.658	*[1.122]*	0.336	*[1.216]*	0.345	*[1.243]*
Lives with other adults, not own child or spouse	0.206	*[0.740]*	0.247	*[0.861]*	-0.142	*[-0.203]*	0.251	*[0.878]*	0.267	*[0.933]*
Lives with own adult child, no spouse	-0.211	*[-1.012]*	-0.202	*[-0.944]*	-0.307	*[-0.437]*	-0.211	*[-0.984]*	-0.191	*[-0.895]*
Number children	0.005	*[0.044]*	0.023	*[0.198]*	0.033	*[0.286]*	0.021	*[0.184]*	0.002	*[0.015]*
Number working adults	0.103	*[0.936]*	0.120	*[1.052]*	0.106	*[0.931]*	0.121	*[1.058]*	0.020	*[0.169]*
Number retirees	-0.016	*[-0.095]*	0.071	*[0.402]*	0.052	*[0.290]*	0.068	*[0.387]*	-0.015	*[-0.084]*
Education 2	0.198	*[1.195]*	0.233	*[1.321]*	0.231	*[1.299]*	0.224	*[1.264]*	0.228	*[1.283]*
Education 3	0.110	*[0.640]*	0.121	*[0.666]*	0.100	*[0.548]*	0.116	*[0.633]*	0.110	*[0.606]*
Education 4	-0.374*	*[-1.722]*	-0.380*	*[-1.671]*	-0.395*	*[-1.730]*	-0.386*	*[-1.695]*	-0.445*	*[-1.958]*
Avg Disc Elig	1.327**	*[2.113]*	1.268**	*[2.225]*	1.255**	*[2.153]*	1.286**	*[2.216]*	1.216**	*[2.125]*
Avg Disc Size	0.002	*[0.185]*	0.002	*[0.183]*	0.002	*[0.219]*	0.002	*[0.164]*	0.002	*[0.217]*
Avg No Drug 1	0.500	*[0.650]*	0.849	*[1.270]*	0.833	*[1.268]*	0.832	*[1.254]*	0.949	*[1.443]*
Avg No Drug 2	-1.323*	*[-1.808]*	-1.634**	*[-2.336]*	-1.676**	*[-2.410]*	-1.622**	*[-2.364]*	-1.675**	*[-2.410]*
Avg Health Pr	1.887*	*[1.662]*	1.521	*[1.365]*	1.591	*[1.494]*	1.504	*[1.463]*	1.631	*[1.559]*
Avg DocVisit	3.325**	*[3.060]*	3.124**	*[2.883]*	3.146**	*[3.007]*	3.113**	*[2.988]*	3.231**	*[3.107]*
Avg Prevention	-5.848**	*[-3.531]*	-5.715**	*[-3.602]*	-5.909**	*[-4.401]*	-5.644**	*[-3.877]*	-5.887**	*[-4.822]*
Avg Hospital	-2.986	*[-0.715]*	-3.160	*[-0.740]*	-3.601	*[-0.821]*	-3.148	*[-1.090]*	-3.032	*[-0.717]*

Table A.3 Drug Purchase Equation: Comparison of Different Income Specifications (Coefficients) - Continued

	No heterogeneity		Time Invariant Heterogeneity - 4 Mass Points: Basic Model		Income Interactions		Log Pension Income Splines		Log Household Income Splines	
Region n	0.023	*[0.031]*	0.095	*[0.128]*	0.063	*[0.084]*	0.081	*[0.125]*	0.092	*[0.126]*
Region c	0.293	*[0.476]*	0.331	*[0.558]*	0.334	*[0.551]*	0.340	*[0.641]*	0.350	*[0.615]*
Region v	0.098	*[0.151]*	0.210	*[0.323]*	0.203	*[0.304]*	0.220	*[0.378]*	0.252	*[0.403]*
Region u	0.746	*[1.116]*	0.789	*[1.178]*	0.796	*[1.160]*	0.789	*[1.284]*	0.826	*[1.268]*
Region ws	-0.311	*[-0.479]*	-0.367	*[-0.558]*	-0.352	*[-0.529]*	-0.357	*[-0.599]*	-0.328	*[-0.517]*
Wegion es	0.345	*[0.506]*	0.338	*[0.495]*	0.351	*[0.504]*	0.334	*[0.541]*	0.338	*[0.509]*
Region ca	0.212	*[0.317]*	0.119	*[0.178]*	0.103	*[0.151]*	0.123	*[0.200]*	0.144	*[0.224]*
Rural	0.284	*[1.620]*	0.213	*[1.186]*	0.204	*[1.135]*	0.219	*[1.217]*	0.199	*[1.104]*
1996	1.297*	*[1.723]*	1.258	*[1.617]*	1.246	*[1.242]*	1.251*	*[1.709]*	1.152	*[1.489]*
1998	0.890	*[1.195]*	0.805	*[0.993]*	0.784	*[0.989]*	0.811	*[1.215]*	0.855	*[1.150]*
2000	0.032	*[0.041]*	-0.181	*[-0.248]*	-0.258	*[-0.351]*	-0.170	*[-0.251]*	-0.237	*[-0.347]*
2001	1.434*	*[1.732]*	1.345	*[1.509]*	1.268	*[1.277]*	1.356*	*[1.657]*	1.274	*[1.414]*
2002	0.105	*[0.154]*	0.067	*[0.102]*	-0.006	*[-0.008]*	0.095	*[0.153]*	-0.060	*[-0.093]*
Constant	-0.093	*[-0.021]*	0.002	*[0.001]*	-0.306	*[-0.066]*	-0.918	*[-0.164]*	1.284	*[0.300]*
Rhocl (Heterogeneity)			2.172**	*[4.395]*	2.146**	*[4.414]*	2.167**	*[4.682]*	2.127**	*[4.367]*

Table A.4: Health Status Equation: Comparison of Different Income Specifications (Coefficients)

	No heterogeneity		Time Invariant Heterogeneity - 4 Mass Points							
			Basic Model		Income Interactions		Log Pension Income Splines		Log Household Income Splines	
Likelihood:	-7769.57		-7552.36		-7547.10		-7548.85		-7541.24	
Log pension	0.296**	*[2.281]*	0.295**	*[2.212]*	0.280**	*[2.029]*			0.288**	*[2.136]*
Lpen spline1							0.231	*[1.089]*		
Lpen spline2							0.231	*[0.397]*		
Lpen spline3							1.201*	*[1.700]*		
Lpen spline4							-0.665	*[-1.137]*		
Pension miss	2.179**	*[2.485]*	2.148**	*[2.379]*	2.105**	*[2.319]*	1.748	*[1.276]*	2.092**	*[2.294]*
Health* log pension					0.038	*[1.128]*				
No spouse* log pension					-0.029	*[-0.743]*				
Adult child* log pension					0.001	*[0.029]*				
Log household income	0.121**	*[3.440]*	0.121**	*[3.172]*	0.141**	*[2.960]*	0.123**	*[3.243]*		
Lhh spline1									0.105**	*[2.230]*
Lhh spline2									-0.077	*[-0.225]*
Lhh spline3									0.935**	*[2.885]*
Lhh spline4									-0.335*	*[-1.797]*
Household inc missing	1.265**	*[3.883]*	1.311**	*[3.681]*	1.253**	*[3.398]*	1.321**	*[3.692]*	1.238**	*[3.205]*
Health* log hhinc					-0.035	*[-0.987]*				
No spouse* loghhinc					-0.020	*[-0.523]*				
Adult child* loghhinc					0.005	*[0.127]*				
Lagged Health	2.030**	*[24.911]*	1.395**	*[10.180]*	1.452**	*[4.294]*	1.378**	*[9.911]*	1.421**	*[10.451]*

Table A.4: Health Status Equation: Comparison of Different Income Specifications (Coefficients) - Continued

	No heterogeneity		**Time Invariant Heterogeneity - 4 Mass Points**							
			Basic Model		**Income Interactions**		**Log Pension Income Splines**		**Log Household Income Splines**	
Drugs Prescribed	-1.241**	*[-6.115]*	-0.216	*[-0.986]*	-0.207	*[-0.962]*	-0.208	*[-0.959]*	-0.227	*[-1.039]*
Drugs Obtained	0.205	*[0.897]*	-0.167	*[-0.722]*	-0.173	*[-0.758]*	-0.172	*[-0.750]*	-0.157	*[-0.680]*
Health * Prescribed	-0.547*	*[-1.914]*	-0.789**	*[-2.789]*	-0.805**	*[-2.854]*	-0.794**	*[-2.785]*	-0.797**	*[-2.826]*
Health * Obtained	0.488	*[1.538]*	0.725**	*[2.350]*	0.726**	*[2.342]*	0.732**	*[2.368]*	0.727**	*[2.366]*
Age	-0.192**	*[-3.428]*	-0.287**	*[-4.194]*	-0.289**	*[-5.147]*	-0.292**	*[-4.159]*	-0.280**	*[-4.071]*
Agesq	0.001**	*[2.267]*	0.001**	*[2.820]*	0.001**	*[3.500]*	0.001**	*[2.848]*	0.001**	*[2.728]*
Lives with spouse, other adults, not own adult child	-0.286	*[-1.391]*	-0.366	*[-1.517]*	-0.366	*[-1.503]*	-0.368	*[-1.520]*	-0.399*	*[-1.669]*
Lives with spouse and own adult child	-0.376**	*[-2.793]*	-0.480**	*[-3.027]*	-0.524	*[-1.563]*	-0.479**	*[-3.014]*	-0.509**	*[-3.218]*
Lives with other adults, not own child or spouse	0.045	*[0.306]*	0.022	*[0.120]*	0.330	*[0.874]*	0.037	*[0.208]*	0.018	*[0.099]*
Lives with own adult child, no spouse	-0.207*	*[-1.735]*	-0.262*	*[-1.859]*	0.024	*[0.061]*	-0.276*	*[-1.942]*	-0.278**	*[-1.973]*
Number children	0.000	*[-0.001]*	0.030	*[0.506]*	0.028	*[0.472]*	0.027	*[0.467]*	0.020	*[0.338]*
Number working adults	0.072	*[1.288]*	0.099	*[1.583]*	0.102*	*[1.653]*	0.099	*[1.564]*	0.099	*[1.536]*
Number retirees	0.072	*[0.783]*	0.153	*[1.472]*	0.146	*[1.422]*	0.150	*[1.423]*	0.147	*[1.415]*
Education 2	0.048	*[0.521]*	0.059	*[0.489]*	0.068	*[0.585]*	0.056	*[0.473]*	0.054	*[0.449]*
Education 3	0.201**	*[2.036]*	0.264**	*[2.109]*	0.264**	*[2.180]*	0.261**	*[2.067]*	0.254**	*[2.073]*
Education 4	0.415**	*[3.217]*	0.537**	*[3.177]*	0.539**	*[3.371]*	0.533**	*[3.171]*	0.515**	*[3.073]*
Avg Health Pr	-1.608**	*[-2.433]*	-1.918**	*[-2.866]*	-1.900**	*[-2.852]*	-1.948**	*[-2.934]*	-1.975**	*[-2.992]*
Avg Doc Visit	1.198**	*[2.057]*	1.110*	*[1.760]*	1.155*	*[1.841]*	1.084*	*[1.716]*	1.113*	*[1.791]*
Avg Prevention	1.813*	*[1.921]*	1.883*	*[1.956]*	1.858*	*[1.931]*	1.931**	*[2.000]*	1.875**	*[1.960]*
Avg Hospital	1.720	*[1.309]*	0.756	*[0.308]*	0.586	*[0.243]*	0.873	*[0.411]*	0.636	*[0.314]*

Table A.4: Health Status Equation: Comparison of Different Income Specifications (Coefficients) - Continued

	No heterogeneity		**Time Invariant Heterogeneity - 4 Mass Points**							
			Basic Model		**Income Interactions**		**Log Pension Income Splines**		**Log Household Income Splines**	
Rural	-0.201**	*[-2.358]*	-0.202**	*[-1.976]*	-0.202**	*[-1.980]*	-0.197*	*[-1.946]*	-0.216**	*[-2.134]*
1996	-0.255	*[-0.667]*	-0.277	*[-0.672]*	-0.272	*[-0.723]*	-0.305	*[-0.810]*	-0.298	*[-0.773]*
1998	-0.155	*[-0.396]*	-0.263	*[-0.623]*	-0.268	*[-0.679]*	-0.223	*[-0.567]*	-0.294	*[-0.728]*
2000	0.613	*[1.498]*	0.554	*[1.229]*	0.556	*[1.348]*	0.562	*[1.348]*	0.519	*[1.226]*
2001	1.241**	*[2.805]*	1.273**	*[2.532]*	1.292**	*[2.876]*	1.274**	*[2.776]*	1.200**	*[2.590]*
2002	0.089	*[0.258]*	0.218	*[0.597]*	0.240	*[0.694]*	0.241	*[0.685]*	0.181	*[0.514]*
Constant	5.246**	*[2.492]*	6.615**	*[2.526]*	6.555**	*[2.906]*	7.174**	*[2.368]*	6.607**	*[2.565]*
Rhocl (Heterogeneity)			4.833**	*[6.418]*	4.755**	*[6.240]*	4.909**	*[6.467]*	4.713**	*[6.606]*

Table A.5: Distribution of Permanent Unobserved Heterogeneity in the Preferred, Jointly Estimated Model with 4 Mass Points

POINT #	PROBABILITY WEIGHT (π)	MASS POINT (μ)
1	0.028	0.000
2	0.519	0.704
3	0.255	0.433
4	0.199	1.000

PROBABILITY WEIGHT (π) RESULTS:

	COEFFICIENT	T-score
PROB WT	2.925	7.091
PROB WT	2.213	6.025
PROB WT	1.966	2.940

MASS POINT (μ) RESULTS:

	COEFFICIENT	T-score
MASS PT	0.866	4.353
MASS PT	-0.271	-1.120

Table A.6: Drug Prescription Equation - Comparison of Four-Equation and Six-Equation Jointly Estimated Models (Coefficients)

	4- Equation Model			**6- Equation Model**					
	Drugs Prescribed All women			**Drugs Prescribed Health Good**			**Drugs Prescribed Health Bad**		
Log pen income	0.524	**	*[3.436]*	0.580	**	*[3.327]*	0.468	**	*[2.469]*
Pension miss	3.520	**	*[3.411]*	3.864	**	*[3.281]*	3.221	**	*[2.513]*
Log household income	-0.032		*[-0.836]*	-0.014		*[-0.262]*	-0.041		*[-0.771]*
Household income miss	-0.269		*[-0.767]*	-0.149		*[-0.297]*	-0.335		*[-0.656]*
Lagged Health	0.292	**	*[2.987]*						
Age	0.352	**	*[4.748]*	0.242	**	*[3.626]*	0.373	**	*[3.707]*
Agesq	-0.002	**	*[-4.229]*	-0.001	**	*[-2.787]*	-0.002	**	*[-3.388]*
Lives with spouse, other adults, not own adult child	-0.008		*[-0.031]*	-0.188		*[-0.560]*	0.331		*[0.881]*
Lives with spouse and own adult child	0.066		*[0.398]*	0.030		*[0.140]*	0.119		*[0.466]*
Lives with other adults, not own child or spouse	-0.290		*[-1.513]*	-0.413		*[-1.619]*	-0.078		*[-0.283]*
Lives with own adult child, no spouse	-0.103		*[-0.700]*	-0.065		*[-0.334]*	-0.152		*[-0.705]*
Number children	-0.088		*[-1.271]*	-0.074		*[-0.819]*	-0.115		*[-1.151]*
Number working adults	-0.090		*[-1.354]*	-0.125		*[-1.383]*	-0.046		*[-0.470]*
Number retirees	-0.275	**	*[-2.473]*	-0.321	**	*[-2.162]*	-0.224		*[-1.426]*
Education 2	-0.086		*[-0.632]*	-0.139		*[-0.801]*	-0.096		*[-0.520]*
Education 3	-0.040		*[-0.286]*	-0.132		*[-0.753]*	0.082		*[0.419]*
Education 4	-0.065		*[-0.362]*	-0.007		*[-0.032]*	-0.412		*[-1.527]*
Avg Prescr	3.249	**	*[2.912]*	4.128	**	*[2.815]*	1.606		*[0.927]*
Avg Disc Elig	-0.045		*[-0.129]*	0.065		*[0.137]*	-0.069		*[-0.131]*
Avg Disc Size	0.000		*[-0.030]*	-0.009		*[-1.241]*	0.009		*[1.110]*
Avg No Drug 1	-0.128		*[-0.284]*	0.284		*[0.498]*	-0.826		*[-1.245]*
Avg No Drug 2	0.810	**	*[2.117]*	0.614		*[1.189]*	0.979	*	*[1.749]*
Avg Health Pr	-1.060		*[-1.505]*	-1.745	*	*[-1.933]*	-0.034		*[-0.034]*
Avg DocVisit	0.471		*[0.734]*	-0.574		*[-0.652]*	1.669	*	*[1.743]*
Avg Prevention	2.880	**	*[3.115]*	4.335	**	*[3.973]*	1.020		*[0.837]*
Avg Hospital	2.805		*[1.448]*	5.745	*	*[1.734]*	-0.703		*[-0.200]*
Region n	-0.031		*[-0.101]*	0.158		*[0.430]*	-0.044		*[-0.106]*
Region c	0.010		*[0.049]*	0.209		*[0.804]*	-0.122		*[-0.400]*
Region v	-0.158		*[-0.674]*	-0.075		*[-0.267]*	-0.373		*[-1.041]*
Region u	-0.198		*[-0.811]*	-0.189		*[-0.635]*	-0.257		*[-0.708]*
Region ws	0.084		*[0.329]*	-0.170		*[-0.545]*	0.450		*[1.167]*
Region es	0.017		*[0.063]*	-0.088		*[-0.265]*	0.148		*[0.379]*
Region ca	0.204		*[0.800]*	0.220		*[0.713]*	0.119		*[0.317]*
Rural	0.103		*[0.806]*	0.135		*[0.868]*	-0.060		*[-0.343]*
1996	0.071		*[0.506]*	0.132		*[0.659]*	0.002		*[0.012]*
1998	0.336	**	*[2.018]*	0.503	**	*[2.226]*	0.157		*[0.640]*
2000	0.443	**	*[2.222]*	0.343		*[1.265]*	0.579	*	*[1.938]*
2001	0.344		*[1.639]*	0.135		*[0.473]*	0.586	*	*[1.893]*
2002	0.331		*[1.489]*	0.247		*[0.836]*	0.446		*[1.345]*
Constant	-15.285	**	*[-5.312]*	-11.798	**	*[-4.569]*	-15.365	**	*[-3.701]*
RHOcl	-6.424	**	*[-7.085]*	-5.743	**	*[-6.020]*	-7.536	**	*[-6.857]*

Table A.7: Drug Purchase Equation - Comparison of Four-Equation and Six-Equation Jointly Estimated Models (Coefficients)

	4- Equation Model			6- Equation Model					
	Drugs Obtained All women			Drugs Obtained Health Good			Drugs Obtained Health Bad		
Log pen income	-0.116		*[-0.574]*	0.057		*[0.193]*	-0.111		*[-0.386]*
Pension miss	-0.665		*[-0.489]*	0.502		*[0.254]*	-0.580		*[-0.298]*
Log household income	0.037		*[0.674]*	-0.055		*[-0.563]*	0.083		*[1.174]*
Household income miss	0.439		*[0.831]*	-0.266		*[-0.280]*	0.838		*[1.258]*
Lagged Health	0.015		*[0.094]*						
Age	-0.091		*[-0.793]*	0.059		*[0.296]*	-0.127		*[-0.874]*
Agesq	0.001		*[0.864]*	0.000		*[-0.304]*	0.001		*[0.976]*
Lives with spouse, other adults, not own adult child	0.250		*[0.638]*	0.726		*[0.858]*	-0.007		*[-0.014]*
Lives with spouse and own adult child	0.332		*[1.225]*	-0.071		*[-0.167]*	0.654	*	*[1.792]*
Lives with other adults, not own child or spouse	0.267		*[0.954]*	1.047	*	*[1.715]*	0.078		*[0.230]*
Lives with own adult child, no spouse	-0.226		*[-1.081]*	-0.121		*[-0.339]*	-0.256		*[-0.947]*
Number children	0.039		*[0.359]*	-0.175		*[-1.105]*	0.265	*	*[1.655]*
Number working adults	0.130		*[1.163]*	0.284		*[1.508]*	0.015		*[0.103]*
Number retirees	0.092		*[0.532]*	0.309		*[1.023]*	-0.044		*[-0.202]*
Education 2	0.217		*[1.256]*	0.108		*[0.374]*	0.331		*[1.491]*
Education 3	0.107		*[0.609]*	0.321		*[1.066]*	-0.082		*[-0.360]*
Education 4	-0.372	*	*[-1.691]*	-0.820	**	*[-2.478]*	-0.033		*[-0.102]*
Avg Disc Elig	1.675	**	*[3.154]*	-0.136		*[-0.158]*	2.833	**	*[3.959]*
Avg Disc Size	-0.004		*[-0.424]*	-0.009		*[-0.569]*	-0.005		*[-0.406]*
Avg No Drug 1	0.538		*[0.837]*	0.471		*[0.495]*	0.391		*[0.489]*
Avg No Drug 2	-1.330	**	*[-2.168]*	-1.758	**	*[-2.073]*	-1.181		*[-1.529]*
Avg Health Pr	1.747	*	*[1.650]*	0.180		*[0.126]*	2.099	*	*[1.649]*
Avg DocVisit	2.252	**	*[2.251]*	3.840	**	*[2.713]*	1.419		*[1.257]*
Avg Prevention	-4.021	**	*[-2.820]*	-2.423		*[-1.313]*	-4.192	**	*[-2.412]*
Avg Hospital	-4.208		*[-1.067]*	-0.521		*[-0.082]*	-5.249		*[-1.005]*
Region n	-0.608		*[-1.593]*	-0.508		*[-0.814]*	-0.690		*[-1.410]*
Region c	-0.016		*[-0.055]*	-0.736		*[-1.629]*	0.371		*[0.987]*
Region v	0.512		*[1.576]*	-0.526		*[-1.081]*	1.073	**	*[2.527]*
Region u	0.099		*[0.297]*	-1.028	**	*[-2.064]*	0.677		*[1.524]*
Region ws	-0.322		*[-0.893]*	-1.500	**	*[-2.782]*	0.350		*[0.740]*
Region es	-0.248		*[-0.675]*	-0.571		*[-0.985]*	-0.111		*[-0.235]*
Region ca	-0.396		*[-1.117]*	-1.728	**	*[-3.256]*	0.320		*[0.687]*
Rural	0.296	*	*[1.727]*	0.009		*[0.031]*	0.585	**	*[2.546]*
1996	-0.124		*[-0.536]*	-0.316		*[-0.863]*	0.002		*[0.008]*
1998	-0.628	**	*[-2.371]*	-0.875	**	*[-2.294]*	-0.334		*[-0.994]*
2000	0.031		*[0.097]*	-0.291		*[-0.630]*	0.252		*[0.617]*
2001	0.944	**	*[2.785]*	1.154	**	*[2.268]*	0.852	**	*[2.014]*
2002	0.573		*[1.624]*	0.477		*[0.962]*	0.615		*[1.383]*
Constant	1.891		*[0.411]*	-1.095		*[-0.136]*	1.721		*[0.295]*
RHOcl	2.181	**	*[4.409]*	1.765	*	*[1.950]*	2.463	**	*[3.660]*

Table A.8: Health Status Equation - Comparison of Four-Equation and Six-Equation Jointly Estimated Models (Coefficients)

	Four Equation Model			Six Equation Model		
Log pen income	0.311	**	*[2.352]*	0.309	**	*[2.268]*
Pension miss	2.279	**	*[2.552]*	2.262	**	*[2.457]*
Log household income	0.124	**	*[3.401]*	0.122	**	*[3.285]*
Household income miss	1.304	**	*[3.841]*	1.282	**	*[3.643]*
Lagged Health	1.395	**	*[10.192]*	1.391	**	*[11.593]*
Drug Prescr	-0.219		*[-1.008]*	-0.243		*[-1.139]*
Drugs Obtained	-0.167		*[-0.739]*	-0.128		*[-0.572]*
Health*prescr	-0.762	**	*[-2.726]*	-0.769	**	*[-2.714]*
Health*purchase	0.708	**	*[2.335]*	0.698	**	*[2.248]*
Age	-0.294	**	*[-4.111]*	-0.286	**	*[-5.606]*
Agesq	0.001	**	*[2.852]*	0.001	**	*[3.790]*
Lives with spouse, other adults, not own adult child	-0.334		*[-1.379]*	-0.357		*[-1.499]*
Lives with spouse and own adult child	-0.466	**	*[-2.940]*	-0.476	**	*[-3.012]*
Lives with other adults, not own child or spouse	0.034		*[0.189]*	0.003		*[0.019]*
Lives with own adult child, no spouse	-0.247	*	*[-1.753]*	-0.246	*	*[-1.788]*
Number children	0.024		*[0.399]*	0.024		*[0.420]*
Number working adults	0.098		*[1.574]*	0.099		*[1.585]*
Number retirees	0.159		*[1.546]*	0.166		*[1.622]*
Education 2	0.049		*[0.415]*	0.060		*[0.524]*
Education 3	0.258	**	*[2.098]*	0.255	**	*[2.106]*
Education 4	0.510	**	*[3.045]*	0.561	**	*[3.361]*
Avg Health Pr	-1.771	**	*[-2.858]*	-1.845	**	*[-2.929]*
Avg DocVisit	1.386	**	*[2.375]*	1.401	**	*[2.416]*
Avg Prevention	1.764	*	*[1.912]*	1.868	**	*[2.024]*
Avg Hospital	-0.302		*[-0.155]*	-0.149		*[-0.072]*
Region n	-0.722	**	*[-2.780]*	-0.743	**	*[-2.888]*
Region c	-0.352	**	*[-1.968]*	-0.370	**	*[-2.088]*
Region v	-0.267		*[-1.416]*	-0.247		*[-1.346]*
Ru	-0.048		*[-0.233]*	-0.050		*[-0.241]*
Region ws	-0.191		*[-0.894]*	-0.205		*[-0.978]*
Res	-0.408	*	*[-1.848]*	-0.412	*	*[-1.902]*
Region ca	-0.125		*[-0.607]*	-0.105		*[-0.526]*
Rural	-0.190	*	*[-1.850]*	-0.154		*[-1.555]*
1996	0.012		*[0.096]*	0.014		*[0.109]*
1998	0.048		*[0.373]*	0.047		*[0.370]*
2000	0.270	**	*[2.101]*	0.264	**	*[2.065]*
2001	0.433	**	*[2.885]*	0.425	**	*[2.862]*
2002	0.308	**	*[2.144]*	0.300	**	*[2.115]*
Constant	6.633	**	*[2.511]*	6.390	**	*[3.134]*
RHOcl	4.824	**	*[6.213]*	4.837	**	*[7.079]*

Table A.9: Distribution of Permanent Unobserved Heterogeneity in the Six-Equation, Jointly Estimated Model with 4 Mass Points

POINT #	PROBABILITY WEIGHT (π)	MASS POINT (μ)
1	0.028	0.000
2	0.267	0.428
3	0.532	0.698
4	0.173	1.000

PROBABILITY WEIGHT (π) RESULTS:

	COEFFICIENT	T-score
PROBWTcl	2.242	6.219
PROBWTcl	2.933	7.713
PROBWTcl	1.807	3.050

MASS POINT (μ) RESULTS:

	COEFFICIENT	T-score
MASSPTcl	-0.290	-1.216
MASSPTcl	0.836	3.883

REFERENCES

Adams, P., Hurd, M., McFadden, D., Merrill, A., Riberio (2003): T. “Healthy, wealthy, and wise? Tests for direct causal paths between health and socioeconomic status,” *Journal of Econometrics*, 112 pp.3-56

Akin, J., Guilkey, D., Griffin, Popkin (1985): <u>The Demand for Primary Health Services in the Third World</u> , New Jersey: Rowman and Allanheld , Chapter 3

Becker, C. and Merkuryeva (2003) I. “Disability Risk in Russia and Kazakhstan,” University of Colorado at Boulder, Research Program on Population Processes, Working Paperr POP2003-0004

Becker, G. (1981): *“Altruism in the Family,”* <u>A Treatise on the Family</u>, Harvard University Press, pp. 277-306

Besstremyannaya, G. (2002): “Differentiation in Accessing Health Care System in Russia,” working paper presented at Global Dev. Network Conference in Prague

Bollen, K., Guilkey, D. and Mroz, T. (1995): “Binary Outcomes and Endogenous Explanatory Variables: Tests and Solutions with Application to the Demand for Contraceptive Use in Tunisia,” *Demography* Vol. 32, No. 1, pp. 111-131

Chapman, K., Hariharran, G. (1994): “Controlling for causality in the link from income to mortality.” *Journal of Risk and Uncertainty*, Vol. 8 No.1, pp. 85-93

Deaton, A. and Paxson, C. (1998): “Aging and Inequality in Income and Health,” *The American Economic Review*, Vol. 88, No.2, pp. 248-253

Duflo, E. (2000): “Grandmothers and Granddaughters: Old Age Pension and Intra-household Allocation in South Africa,” Mimeo, MIT

Dwyer, D. and Mitchell O. (1999): “Health Problems as Determinants of \Retirement: Are Self-rated Measures endogenous?” *Journal of Health Economics*, 18, pp. 173-193

Ettner, S. (1996): “New Evidence on the Relationship between Income and Health,” *Journal of Health Economics*, 15, pp. 67-85

Feeley, F (1999): “Could Drug Costs be Contributing to Cardiac Mortality in Russia?” Boston University School of Public Health, working paper

Fuchs, V., McClellan, M., Skinner, J. (2001): “Areas Differences in Utilization of Medical Care and Mortality among U.S. Elderly,” NBER working paper 8628

Foley, M. (2003): “The Elderly in Russia: Pension Arrears and Survival Mechanisms,” Dept. of Economics, Davidson College, preliminary draft

Gilleskie, D. (1998): “A Dynamic Stochastic Model of Medical care Use and Work Absence,” *Econometrica*, Vol. 66, No.1, pp. 1-45

Grossman, M. (1972): "On the concept of health capital and demand for health," *Journal of Political Economy,* Vol. 80, No. 2, pp. 223-255

Gurvich, E. (2004): "The Distributional Aspects of the Russia's Pension System," Research Paper Produced by: Economic Expert Group, Russia

Heckman, J. and Singer, B. (1984): "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data," *Econometrica*, Vo. 52, No. 2, pp. 271-320

Institute of Social Research (1999): *Russian Household Drug and Health Care Expenditures Social Survey Finding*, Moscow

Jensen, R. and Richter K. (2003): "The Health Implications of Social Security Failure: Evidence from the Russian Pension Crisis." *Journal of Public Economics* 88, pp. 209 -236

Katz, S., A. Ford, R. Moskowitz, B. Jackson and M. Jaffe (1963): "Studies of Illness in the Aged," *Journal of the American Medical Association,* September 21 pp.94-9.

Norburn, K. et al. (1995): "Self-Care and Assistance from Others in Coping with Functional Status Limitations Among a national Sample of Older Adults," *Journal of Gerontology: Social Sciences*, Vol. 50B, No. 2, pp. 101-109

Lokshin, M, and Ravallion, M. (2008): "Testing for an Economics Gradient in Health Status Using Subjective data," *Health Economics,* forthcoming

Lushkina, N. (2001): "Social, Medical and Demographic Problems of the Elderly," Ph.D. dissertation in Economics, Moscow, Russia

McDonough, P. et al. (1997): "Income Dynamics and Adult Mortality in the United States, 1972 through 1989," *American Journal of Public Health*, Vol. 87, No. 9, pp. 1476-1482

Meer, J., Miller, D. and Rosen, H. (2003): "Exploring the Health – Wealth Nexus," *Journal of Health Economics*, VOl. 22, pp. 713-730

Mroz, T. (1992): "Discrete Factor Approximation in Simultaneous Equation Models: Estimating the Impact of a Dummy Endogenous Variable on a Continuous Outcome." *Journal of Econometrics* 92, pp. 233 – 274

Mroz, T. Henderson, L. and Popkin, B.M. (2001): "Monitoring Economic Conditions in the Russian Federation: The Russia Longitudinal Monitoring Survey 1992-2000." Report submitted to the U.S. Agency for International Development. Carolina Population Center, University of North Carolina at Chapel Hill, North Carolina.

Lundberg, S., Pollack, R. and Wales, T. (1997): "Do Husbands and Wives Pool Their Resources?" *The Journal of Human Resources*, Vol. 32 No. 3, pp. 463-480

Philipson, T. and Becker, G. (1998): "Old Age Longevity and Mortality-Contingent Claims." *Journal of Political Economy*, Vol. 106 No.3, pp. 551-573

Pezzin, L and Schone, B.S. (1997): "The Allocation of Resources in Intergenerational Households: Adult Children and Their Elderly Parents," *The American Economic Review*, Vol. 87 Issue 2, Papers and Proceedings of the 104th Annual Meeting of the AEA, pp.460-464

Samuelson, P. (1956): "Social Indifference Curves," *Quarterly Journal of Economics,* Vol. 70, pp.1-22

Schultz, J. P. (1990) "Testing the Neoclassical Model of Family Labor Supply and Fertility," *The Journal of Human Resources*, Vol.25, Issue 4, pp.599-634

Shishkin, S.V. (2000): Health Care Financing Reform in Russia. Moscow, Teis.

Shkolnikov, M. et al. (1998): "Causes of the Russian Mortality Crisis: Evidence and Interpretations," *World Development,* Vol. 26, No. 11, pp. 1995-2011

Smith, J. and Kington, R. (1997): "Demographic and Economic Correlates of Health in Old Age," *Demography*, Vol. 34, No. 1, pp. 159-170

Smith, J. (1999): "Healthy Bodies and Thick Wallets: The Dual Relationship between Health and Economic Status," *The Journal of Economic Perspectives*, Vol.13, No.2, pp.145-166

Smith, J. and Kington, R. (1997) "Race, Socioeconomic Status and Health in Late Life," in L, Martin and B. Soldo (eds) *Racial and Ethnic Differences in the Health of Older Americans*, National Academy Press: Washington, pp. 106-162

Stillman, S. (2001): "The Response of Consumption in Russian Household to Economic Shocks." IZA Discussion Paper Series, IZA DP No. 411

Stillman, Steven & Thomas, Duncan (2004): "The Effect of Economic Crises on Nutritional Status: Evidence from Russia," IZA Discussion Papers 1092, Institute for the Study of Labor (IZA).

Strauss, John & Thomas, Duncan (1995): "Human resources: Empirical modeling of household and family decisions," in: Hollis Chenery† & T.N. Srinivasan (ed.), Handbook of Development Economics, edition 1, Elsevier, Volume 3, chapter 34, pp. 1883-2023

Street, A, Jones, A. and Furuta, A. (1999): "Cost-sharing and Pharmaceutical utilization and expenditure in Russia." *Journal of Health Economics* 19, pp. 459-472

Thomas, D. (1990): "Intra-Household Resource Allocation: An Inferential Approach," Symposium on Household Bargaining Models *The Journal of Human Resources*, Vol. 25, No. 4., pp. 635-664

Thomas, D. and Strauss, J. (1997): "Health and Wages: Evidence on men and women in urban Brazil." *Journal of Econometrics*, 77 , pp. 159-185

World Health Organization (1998): *Health Care Systems in Transition – Russian federation*, Regional Office for Europe, Copenhagen

World Health Organization (1998): *The Patient in Focus – A Strategy for Pharmaceutical Sector Reform in Newly Independent States*, Office for Europe, Copenhagen

Yang, Z., Gilleskie, D. and Norton. E. (2004): “Prescription Drugs, Medical Care, and Health Outcomes: A Model of Edlerly Health Dynamics,” preliminary paper

Zohoori, N, Gleiter, K, and Popkin, B.M. (2001): "Monitoring Health Conditions in the Russian Federation: The Russia Longitudinal Monitoring Survey 1992-2000." Report submitted to the U.S. Agency for International Development. Carolina Population Center, University of North Carolina at Chapel Hill, North Carolina